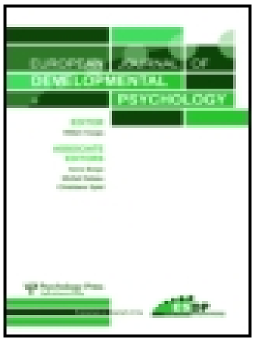

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Unsupervised categorization with a child sample: category cohesion development

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ABSTRACT

Studies into categorization have demonstrated that the ability to form concepts is an essential ability in cognitive development. For example, before a decision about anything can be made, firstly category concepts need to be acquired in order to make efficient decisions about that situation. The present study explored a particular type of category learning, not previously explored in this particular context – unsupervised categorization with 16 items and two dimensions, and comparing specifically children vs. adults. Previous studies have typically focused on simpler designs such as three items of two dimensions in the triad tasks, or a greater number of dimensions but with much fewer items per category in other unsupervised settings. This study investigated unsupervised categorization with two levels of task difficulty, and compared two different populations, children and adults. The findings revealed that adults performed better for the easy condition but there was no difference between these groups for the more difficult category task. The findings also revealed that unsupervised categorization in more complex settings result in more one dimensional sorting, for both children and adults. The results are discussed in the context of unsupervised categorization development abilities in children.

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KEYWORDS Unsupervised categorization; development; cognitive; over-selectivity

Category learning is fundamental to all aspects of decision-making, as one needs to acquire concepts about properties in the environment in order to make adequate decisions about these, i.e., there is little more basic and fundamental level in processing informvation about the environment (e.g., Lakoff, 1987, p. 5; Laurence & Margolis, 1999). However, the vast majority of studies in categorization have explored category learning in adult populations. There are, however, a few exceptions such as some studies which have explored category induction through linguistic labels (Sloutsky & Fisher, 2004); improvements in categorizing novel objects using shared category labels (Graham, Namy, Gentner, & Meagher,

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2010); and categorical face discrimination of children (Anzures, Quinn, Pascalis, Slater, & Lee, 2010), but these have used category labels and are examples of supervised categorization tasks as opposed to the measures of intuitive coherence of novel similarity structures (i.e., unsupervised categorization tasks).

Categorization, generally, in the literature, has primarily two distinct theoretical streams, and one emerging one. These are (1) supervised categorization theories (e.g., Hampton, 2007; Kurtz, 2007; Minda & Smith, 2000; Nosofsky, 1988; Vanpaemel & Storms, 2008). (2) Unsupervised categorization theories, e.g., the simplicity model (Pothos & Chater, 2002; Pothos, Edwards, & Perlman, 2011b; Pothos et al., 2008 Pothos et al., 2011a). Also, (3) a newer emerging area, relational representation in categorization theories (e.g., Edwards, 2015; Edwards, Pothos, & Perlman, 2012; Stewart, Brown, & Chater, 2005; Zentall, Galizio, & Critchfied, 2002).

Supervised category learning involves the study of how people learn to decide which items belong to which categories, when already given the category structures for the categories, e.g., the participant is told which items belong to category A and category B, and then they must decide which categories new items must belong to. In relational categorization experiments (which also uses supervised learning), the experimenter is exploring in what conditions do emergent relational (analogical mapping type) decisions occur. The participant is given the two categories, for example, just like in supervised categorization, but the categories are structured in a way which shift the participant away from simple similarly decisions, to more complex relational ones (e.g., bigger vs. smaller).

In unsupervised category learning (the paradigm used in this paper), the procedure is very different to supervised categorization. In this task, the participants are not given any categories, they are simply given several items and are asked to put these into whatever groups they want to, i.e., they cannot infer from any pre-selected categories by the experimenter (such as in supervised categorization). Unsupervised categorization, therefore, comes from a largely different set of literature (as compared to supervised categorization literature), which involves theories of category coherence (e.g., Murphy & Medin, 1985; Rosch & Mervis, 1975). Category coherence relates to how intuitive the structures being categorized are, and how easy they are to categorise, without any knowledge about what the categories should look like (which, again, is different to supervised categorisation).

Further to this, there are also several computational models used by categorization researchers in both supervised and unsupervised categorisation studies, which can demonstrate the most 'efficient' means of category clustering, when given several multi-dimensional stimuli in any given experiment. These efficient categories can, for example, be regarded as 'optimal' in the literature, from a computational, information reductionism perspective (e.g., see the simplicity model, Pothos & Chater, 2002). In addition to the simplicity model work mentioned (Nikolopoulos & Pothos, 2009; Pothos & Chater, 2002), there are several other computational models for unsupervised categorization which are worth mentioning. For example, Gureckis and Love (2004) developed SUSTAIN, which is a connectionist model (a neural network) for category learning, and has both unsupervised and supervised components. There is also Anderson's (1991) rational model, which takes the dimensions of a given item and identifies the probability of which category the item should belong to based on how similar its features are with that of the dimensions of items in existing categories. Another unsupervised category model is Rumelhart and Zipser's (1985) competitive learning, feature detector, neural network. Also, out of the completive learning literature, developed Carpenter and Grossberg (1998) ART model, which is an adaptive resonance theory, based on the stability-plasticity dilemma. This dilemma presents the problem of how a learning system can remain adaptive or plastic in response to significant events, but stable against irrelevant ones. In doing this, a self-organising neural network organises in real time when given arbitrary sequences of input patterns.

In addition to these computational models, there have also been some studies which have explored unsupervised categorization specifically with child populations, but to be clear these are very different to the paradigm being proposed here for this present study. For example, the triad tasks of Smith and Kemler (1977) used three items of two dimensions, whilst the present study used 16 items of two dimensions. The only exception to this is the study by Nikolopoulos and Pothos (2009) who also used a 16 item per set, with two dimensions (the same as the present study). However, there are some crucial differences between the present study and that one, namely in the population comparison and the way in which the categories were analysed. Nikolopoulos and Pothos (2009) opted to use the simplicity model to compute category efficiency based on the simplicity model with a child dyslexic vs. a child control population. This type of analysis is very different to the feature discrimination tasks employed in this current paper (and the type of analysis conducted by many of the discrimination studies, such as the triad tasks). For the present investigation, instead of this simplicity approach analysis, the much simpler analysis of feature discrimination has been used. Specifically, the present study uses a very similar approach to Milton, Longmore, and Wills (2008).

One of the justifications made by Nikolopoulos and Pothos (2009) to use the simplicity model, may have been because of the complexity and huge number of possible classifications made, i.e., it is difficult to categorise items into strict one and two dimensions when so many possible classification can be made. It can be difficult to determine what happens with all these other non-one or two dimensional sorts. Despite this difficulty, it is, however, equally important to use standard feature discrimination tasks in these more complex unsupervised tasks, so as to compare outcomes with some of the simpler (fewer item and features) feature discrimination tasks, such as the triad tasks.

To explain these triad tasks studies in more depth, from the unsupervised categorization literature (e.g., Smith and Kemler, 1977). These studies assessed whether the individual child/infant uses individual features or overall similarity in the categorization of items, when there is no learning involved. From these studies, it is suggested that children should use both dimensions (overall similarity). However, there are many studies which suggest the contrary. Studies on sensitivity to correlation suggest that infants use feature correlations (single feature dimensions) and not overall similarity (e.g. Gureckis and Love, 2004; Younger & Cohen, 1986) and studies into category construction (Younger & Mekos, 1992), also suggest that children use features. So, many studies suggest that children should categorise on the basis of a single dimension, except in the case of the triad tasks. It should also be noted that Thompson (1994), also Raijmakers, Jansen, and van der Maas (2004), have suggested that the findings of many of the triad tasks were due to an inappropriate analysis method, and that actually the findings suggest that the children were categorising according to a single dimension, and not to overall similarity as suggested by these studies.

So, the present study is novel as it explores unsupervised categorization in a different context, i.e., using discrimination based analysis and not computational models, for very complex stimuli, and not simple stimuli sets. To do this, a comparison is made between healthy child and adult population. In a typical unsupervised task, several stimuli are placed in front of a participant and they are asked to sort these into groups without being told anything about which items should belong together, i.e., they are not given any categories. In these types of tasks, it is important that all the necessary dimensions need to be attended to by the participant otherwise problematic category formations can result, for example, placing attention to only one dimension such as the length or width of the items rather than both dimensions (see Figure 1 for an example of the stimuli used). This problematic categorization is the process of over-selectivity (or one dimensional sorting), and in recent studies (Edwards, Perlman, & Reed, 2012) have demonstrated that problems can occur with this type of categorization task when using autistic populations as the autistic children tend to just focus on one of the dimensions, e.g., body or legs (length or width) of the items. It is also interesting to note that over-selectivity can also be simulated in a normal population through providing concurrent tasks such as a discrimination task and a concurrent visual spatial task (Reed & Gibson, 2005). It should also be noted that the term over-selectivity is synonymous with single-dimensional sorting, as also used in the literature (e.g., Milton et al., 2008).

As a prediction, in this study, it is likely that both the adults and children will over-select in a difficult categorization task as they have done so in difficult discrimination tasks (Reed & Gibson, 2005). However, given that children have under-developed attentional skills (e.g., Irwin-Chase & Burns, 2000; Karatekin, 2004), rely on linguistic labels (Sloutsky & Fisher, 2004), on shared labels (Graham et al., 2010) have difficulty in discriminating categories of faces

(Anzures et al., 2010), it may be reasonable to predict they will have greater difficulty in attending to both dimensions, as compared to an adult population, for the more easy categorization task, thus displaying greater over-selectivity (just using one instead of two dimensions in categorizing).

Method

Participants

36 Children with a mean age of 9.21 (SD = 0.92) were recruited from local schools. This was compared against 36 adults with a mean age of 21.32 (SD = 1.12) who were recruited from the local community (a university student sample was avoided to prevent any population bias).

Defining one vs. two dimensional sorting – the measure for over-selectivity

For this study, the approach used in Edwards, Perlman et al. (2012) was used to assess over-selectivity (one-dimensional sorting) in an unsupervised categorization task. This approach is similar to that of Milton et al. (2008). In this procedure, a one dimensional classification could only occur if an item was categorised outside of the preferred classification (see Figure 2) in a way where it was identical to a single dimension of another item in another category. Items which were classified to neighbouring items but not identical to either dimension were considered an overall classification (two dimensional). These items had to be categorised in the same way as the existing categories as predicted by the simplicity model, for the preferred categories (see Figure 2). Items that were categorised to other categories, which were different to what the simplicity model predicted, but also were not identical to other items in other categories across a single dimension were classified as random, and items categorised by themselves were also classified as random.

The reason for adopting this approach is that Thompson (1994) has highlighted the problem with previous types of analysis in unsupervised categorization work, such as the triad tasks (e.g., employed by Gibson, 1979; Smith and Kemler, 1977) indicting that children are categorizing through overall similarity. However, as Thomson points out, this was actually clearly an artefact of inappropriate analysis (a similar point was also identified more recently by Wills, Inkster, & Milton, 2015). Raijmakers et al. (2004) have a potentially better form of analysis when interpreting overall similarity. However, this relies on the use of very large sample sizes, which are difficult to obtain. Therefore, the preferred method for analysis is that based on Milton et al. (2008).

To make this analysis explicit, through use of an example, the simplicity model (which in this case makes use of both dimensions to determine categories) suggests that the preferred classification for the Easy set is; [0, 1, 2] [6, 7, 8] [5, 3, 4] [11, 9,10] [12, 13, 14, 15]. Items which are classified within these preferred categories would be classified as overall similarity (two dimensional). If an item was categorised outside of these strict groupings, then it would be classified as either a random sort, or a one dimensional sort, depending on where it was categorised. In the instance; [0, 1, 2, 10] [6, 7, 8] [5, 3, 4] [11, 9] [12, 13, 14, 15], the 10 is clustered with 0, 1 and 2. Clearly the x axis (see Figure 2), body, is not being used, therefore only a single dimension is being used (legs). 10 is identical to 1 and 2 on a single dimension, so this would be counted as a one-dimensional sort (one count of over-selectivity). In another situation, clusters such as [0, 1, 2] [6, 7, 8] [5, 3, 4, 15] [11, 9,10] [12, 13, 14], where 15 is clustered with 5, 3, and 4. This would be classified as random, as there is no identical dimension in the items of the category which it has been placed. Also, in the case of [0, 1, 2] [6, 7, 8] [5, 3, 4] [11, 9] [12, 13, 14, 15] [10] where 10 is categorised by itself, this would be classified as a random sort as it is not clear what dimensions have been used in this instance. It should also be noted that it is only the optimal categories (i.e., the preferred, see Figure 2) which are considered when making decisions about over-selectivity, as these are most efficient, so other less efficient categories are not included and therefore have no impact on the DV of over-selectivity in this setting.

Materials

Categorization stimuli

For this study, the stimuli and procedure were identical to those employed by Pothos et al. (2008), Pothos et al. (2011a), Pothos et al. (2011b) and Edwards, Perlman et al (2012), except that only two of the stimuli sets are used. The stimuli were created which resembled spiders, and had two relevant features, the body and the legs. The sizes of the legs and body were altered, between 40 and 80 mm (using a Webber fraction of 8%), so that the stimuli sets were presented in terms of different levels of how intuitive these were (i.e., low intuitiveness and high intuitiveness). See Figure 1 for an example of the stimuli that was used.

In Pothos et al. (2008) they used the simplicity model to predict category intuitiveness in unsupervised categorization, and how easy it would be to categories each stimulus set. When given a set of stimuli based on two dimensions (legs and body), the model predicts how best the categories (or clusters) should be organized. This organization by the model (codelength) is a complex term, referring to computational complexity, and the reduction of codelength, where maximum within group similarity and minimum between group similarity is sought (see Pothos et al., 2008). The suggested categories by the model correspond to how participants without cognitive deficits should categories these items using both dimensions of the stimuli. For the present paper, the only concern are these suggested categories (see Figure 2) produced by the simplicity model on the basis of two dimensions, and not how the computational term is produced.

Procedure

The participants were required to enter the laboratory individually. Once there, stimuli were removed from a folder, and presented in random order (i.e., they had been shuffled), by spreading them out on a large table, so that the participant could see all of the items at once. Instructions were provided which asked the participant to categorize the items in a way they felt was most intuitive, and this should be based on how similar they were. They were also instructed that similar objects should be categorized in the same categories and that there were no limit to how many categories there should be. There was no time limit on this task, however, the task typically did not last more than a few minutes. Participants were not influenced in how they made the categories, and were redirected to the instruction if they asked any questions. The stimuli sets were always shuffled after each participant and then put back into a folder. The sets were also counterbalanced between participants to prevent any order effects.

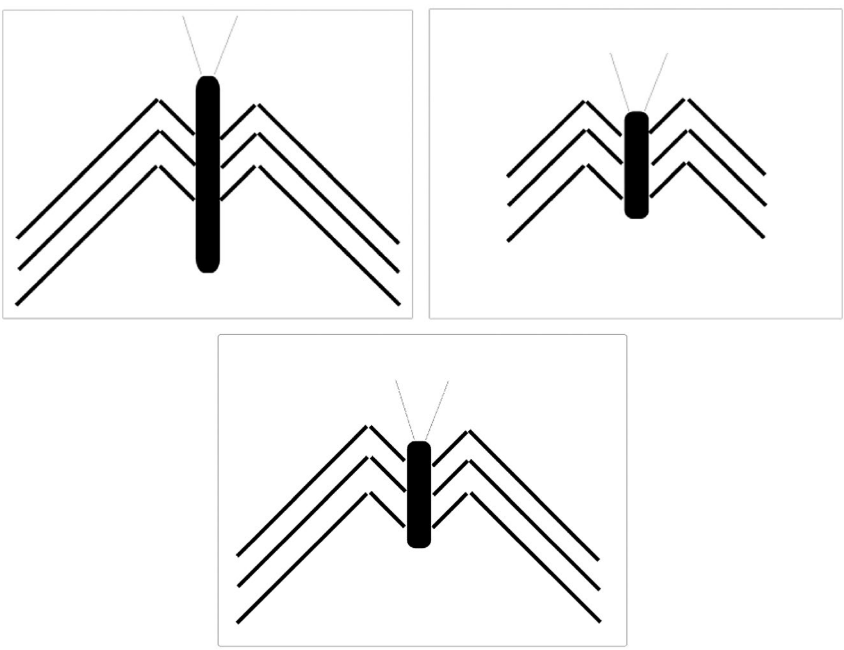

Figure 1. Stimuli used, with different sized bodies and legs.

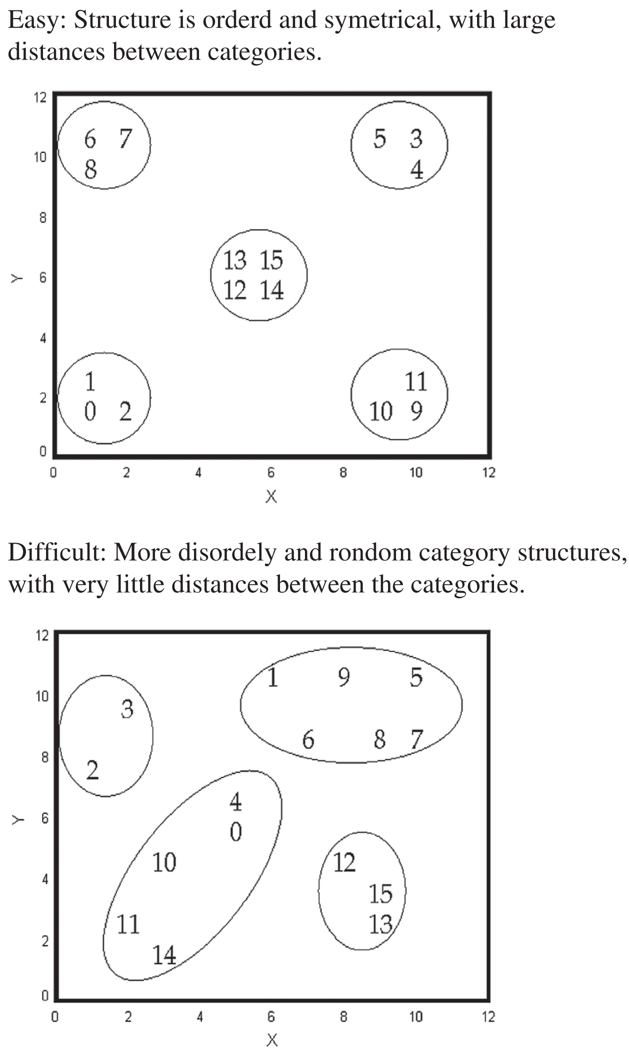

Figure 2. The simplity models' interpretation of what constitutes the most efficient categories.

Results

Figure 3 demonstrates the mean and standard error of the over-selective responses for the child and adult groups for both the easy and difficult category conditions (please see this link for the trial level raw data: http://darrenedwards.info/index_files/raw%20data%20child%20vs.%20adult%20overselectivity1.xlsx).

On inspection of the data, it appears that in general both children and adults performed worse for the more difficult categorization task (i.e., they had a higher

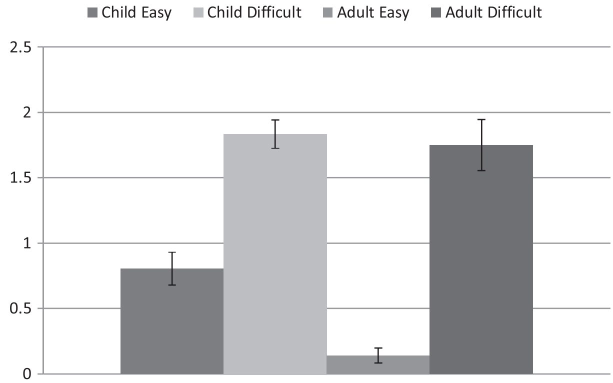

Figure 3. Mean and standard error of over-selcivity in child and adult populations.

proportion of over-selectivity) as compared with the easy group. In terms of the difference between child and adult performance, it appears that only in the easy condition did children perform worse (i.e., through greater over-selectivity).

A two way mixed ANOVA (2 × 2) revealed that the main within subject effect for task difficulty was highly significant, $F(1, 70) = 100.25$, $p < 0.001$. The main between subject effect of child or adult was significant to $F(1, 70) = 8.07$, $p < 0.05$. The interaction between task difficulty and population type was also significant, $F(1, 70) = 4.89$, $p < 0.05$.

A further *t*-test analysis on this interaction revealed that only the easy task difficulty was significant (Bonferroni corrected) for the between groups, child and adult $t(70) = 4.84$, $p < 0.001$. Though children had a marginally greater number of over-selective responses for the difficult condition, this was not significant, $t(70) = 0.37$, $p = 0.36$.

Discussion

This study explored whether there would be any performance difference (in terms of levels of over-selectivity) between children and adults in an unsupervised categorization task. The results revealed that whilst both groups made more over-selective responses in their category decisions for the more difficult category condition, it was only for the easier category condition that there was a significant difference between children and adults, where the children demonstrated more over-selective responses.

This study's findings are important for three reasons. Firstly, it demonstrates that children do have difficulty with categorizing even relatively easy unsupervised category structures, indicating under-developed category cohesion, and attentional resources (e.g., Murphy, & Medin, 1985; Rosch & Mervis, 1975), and greater over-selectivity (e.g., Edwards, Perlman et al., 2012; Reed & Gibson, 2005). Secondly, the results also have implications for understanding the cognitive development of children, where a demonstration that children over-select more than adults in an unsupervised categorization task, which indicates that cognitive similarity abilities for this type of categorization task are still in development during childhood. Thirdly, this supports findings from the literature on sensitivity to correlation, which suggest that infants use feature correlations (single feature dimensions) and not overall similarity (e.g. Gureckis and Love, 2004; Younger & Cohen, 1986) and studies into category construction (Younger & Mekos, 1992) which again demonstrated that children tend to use one dimensional features in categorizing and not overall similarity. This explanation is also consistent with that of Gureckis and Love (2004) and Reed and Gibson (2005) which suggest that attentional and memory limitations lead onto greater numbers of one dimensional sorting.

These findings could have important applied implications in terms of understanding many different types of developmental learning, for example the ability to learn concepts which are crucial for effective decision-making. This could be useful in understanding particular cognitive deficits in children with learning difficulties, and could help lead onto the development of interventions to remediate these deficits, and tailor-make specific educational curriculum for these individuals. However, in order to explore this effectively and more specifically, many further categorization experiments would need to be carried out which explore additional developments in categorical learning, specifically in the areas of unsupervised as well as further supervised categorization studies. These would need to include different modalities, other than shape, such as colour, semantics etc., and explore how these tasks could be used to screen for particular deficits (such as the application in Edwards et al., 2012) or give further understanding in the developmental process during childhood.

In addition to this, further attempts to integrate the findings of other categorization work, in the supervised literature of childhood development, could be useful, such as the works of Sloutsky and Fisher (2004); Graham et al. (2010); Anzures et al. (2010) and the relational categorization work of Edwards, Perlman et al. (2012). Such attempts could lead to a more universal model of childhood categorization skill development.

On the whole, this present research offers some interesting insights into children's ability to categorize two dimensional items with complex stimuli sets, which could have potential implications in how they develop more complex concepts. This research offers a good starting point for further studies into child unsupervised categorization abilities, for complex stimuli sets. In the future, more studies could explore many of the different types of categorization paradigms mentioned in this discussion and integrate findings to develop a more complete model for child cognitive development. Only then would a fuller understanding of how childhood categorization ability emerges into adulthood, and what are the greater implications of such learning skills.

Disclosure statement

No potential conflict of interest was reported by the author.

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