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Visual Strategies in Analogical Reasoning Development: A New Method for Classifying Scanpaths

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Abstract

Development of analogical reasoning is often explained by general maturation of executive functions. A consequence of the involvement of executive functions would be that children and adults differ in the visual strategies they apply when solving analogical problems. Since visual strategies can be studied by means of eye-tracking, we compared the visual scanpaths of children and adults in three different analogical reasoning tasks. This comparison was done by means of a novel technique that combined a recently developed algorithm for computing a “distance” between any pair of scanpaths (Jarodzka, Holmqvist, & Nyström, 2010), multidimensional scaling (MDS), and a neural network classifier. This analysis clearly showed a difference between adults' and children's visual strategies in solving analogy problems. We focus both on the demonstration that adults and children employ different visual search strategies to solve analogy problems and on the novel technique used to do this. This general technique complements other approaches to eye-movement analysis that rely on local properties of scanpaths, in particular, item-fixation times.

Keywords: Analogical reasoning; development; eye-tracking; strategies.

Introduction

Analogical reasoning is a ubiquitous process in thinking and reasoning (Gentner & Smith, 2012; Holyoak, 2012). It can be defined as a comparison of two domains (the source and the target domains) on the basis of their respective relational structure (Gentner, 1983). Studies of analogy making have explored two main explanations for its development, increase of structured knowledge (Gentner & Rattermann, 1991; Goswami, 1992) and maturation of executive functions (Halford, 1993; Richland, Morrison, & Holyoak, 2006; Thibaut, French, & Vezneva, 2010a, 2010b). One important prediction of the executive-function view is that children and adults use different strategies when solving analogy problems. The present study addressed this question by means of a combination of a recently developed algorithm (Jarodzka et al., 2010) for comparing visual scanpaths from an eye-tracker, multi-dimensional scaling (MDS), and a neural net classifier. This technique allowed us to give an affirmative answer to the central question of this paper — namely, whether or not children's analogy strategies are quantifiably different than those of adults.

Background

Humans rely heavily on vision for virtually every task they do (e.g. categorization, spatial orientation, problem solving, etc.) and it remains a privileged way of acquiring information about the environment. In the case of problem solving, what information is sought and how this search is organized through time to come to a solution for the problem (i.e. visual strategies) may help researchers understand which solving strategies are used. Attention and gaze-fixation are highly correlated, especially for complex stimuli (Deubel & Schneider, 1996; He & Kowler, 1992) and the fixation time for a given object is correlated with its informativeness in a scene (Nodine, Carmody, & Kundel, 1978). This argues in favor of studying eye-movements as indicators of the application of a specific strategy through control of attention.

Eye-tracking data, especially if they involve scanpaths — i.e., the complete visual trajectory of a participant's eye movements during the task — are often complex and hard to analyze. For this reason scanpath information is often reduced to static information about the participant's gaze times at specified locations. This simplification, while certainly easier to analyze, generally fails to fully capture the temporal aspects of the data involved in visual strategies. Even when an attempt is made to take into account temporal aspects of the data, it is often difficult to compare two scanpaths because, in general, they differ in length and complexity. Jarodzka et al. (2010) have developed a method that is able to compare any two scanpaths. As the Jarodzka et al. algorithm plays a key role in the analysis that follows, we will describe our variant of this algorithm in some detail below. We combined this scanpath-comparison algorithm with multidimensional scaling and a neural-network classifier to demonstrate that children's analogy-making strategies, as reflected in their visual search patterns across three different problems, are measurably different from those of adults.

We are not the first to use eye-tracking technology to study analogy making, but this type of analysis is, nonetheless, still in its infancy. Eye-tracking techniques were first used by Bethell-Fox, Lohman, & Snow (1984) to study strategies when reasoning by analogy. They found strategic differences in adults with high or low fluid

intelligence when solving geometric $A:B::C:?$ problems. More recently, Gordon & Moser (2007) investigated adults' strategies in scene analogy problems. Thibaut, French, Missault, Gérard, & Glady (2011) also used an eye-tracker to examine infants' gaze locations and item-to-item transitions during an analogy task. However, all of these studies focused on what information was searched for by participants as they attempted to solve the analogy problem.

None of this research compared participants' global scanpaths. In other words, previous eye-tracking studies have focused on local aspects of participants' scanpaths as a means of revealing part of the dynamics of visual search in doing analogy problems. By contrast, in the present study we will use participants' global scanpaths in our attempt to respond to the question of whether children have different visual search strategies than adults when solving visual analogy problems. Woods et al. (2013) showed that the organization of search in visual-attention tasks becomes less variable over the course of development. Because the tasks we used rely on visual attention, we expected children to have more variable scanpaths than adults.

Experiment

Methods

Participants

Subjects were 20 adults (14 females, 6 males; mean age=20;5 years; SD=2.21; range: 17 to 27), students at the University of Burgundy and naïve to analogical reasoning tasks and 26 6-year-olds (16 females, 10 males; mean age=79.5 months; SD=3.6; range: 73 to 84). For children participating in this experiment, parents' informed consent was required from their parents.

Materials

Three tasks, each composed of three training trials and four experimental trials, constituted the experiment (see Figure 1). The first task was a scene analogy problem task, the second a standard $A:B::C:?$ task and the third an $A:B::C:?$ task with the items composing the problems put within a context. Each problem of each task was composed of 7 black and white line drawings.

In the scene analogy problems, the top scene was composed of two elements depicting a binary semantic relation (e.g. a cat chasing a mouse). One of these two elements had an arrow pointing to it. The bottom scene was composed of five drawings: the two elements depicting the same relation as in the top picture (e.g. a boy chasing a girl), a distractor item, and two elements that were consistent with the scene but that had no salient relation with the elements of the relation. These pictures (501x376 pxs) were based on Richland et al., (2006) except for the distractor that was chosen not to be perceptually, only semantically, related to one member of the relation in the bottom picture.

In the standard $A:B::C:?$ trials, the A, B, C drawings were presented in the top row along with a black empty square symbolizing the location of the solution. The four remaining pictures (the Target, a Related-to-C Distractor, and two Unrelated Distractors) were presented in a row at the bottom of the screen. The size of each picture was 200x195 pxs. The $A:B::C:?$ task within context was constituted of two scenes (501x376 pxs). The top picture was composed of two black and white line drawings with a relation between them (e.g. a wolf and meat, with the wolf looking at the meat) with a contextual cue (e.g. a horizontal line for the horizon or the lines of the joining walls and floor for a room). The bottom picture was composed of the five remaining drawings: the C term, the Target, the Related-to-C Distractor and the two Unrelated Distractors. This task differed from the first task in that it was the C term that was

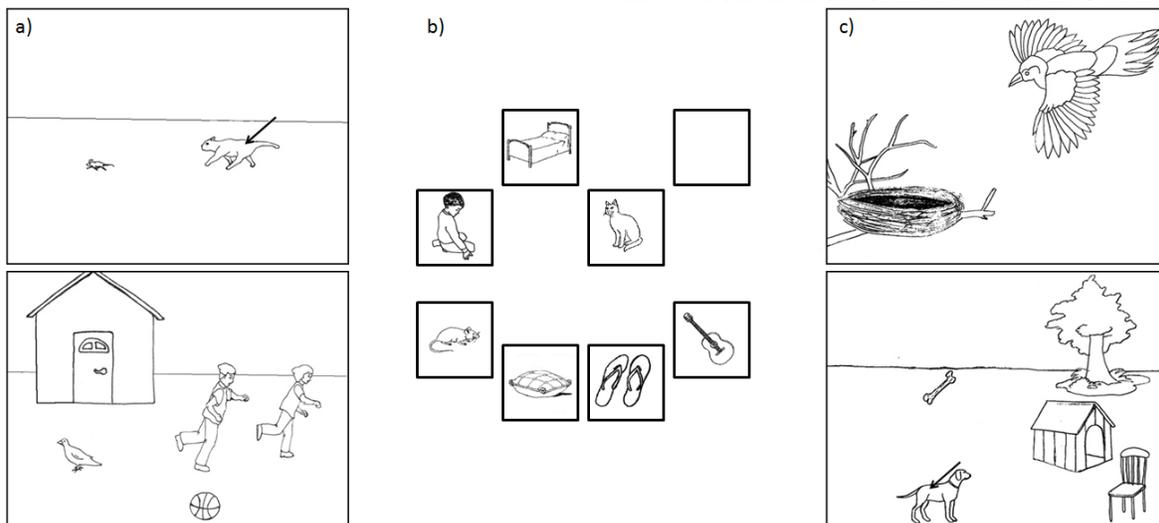


Figure 1. Presentation of the three tasks used for this experiment: a) scene analogy task, b) standard $A:B::C:?$ task, c) scene-oriented $A:B::C:?$ task

pointed at with an arrow, and not one of the elements constituting the source relation. It differed from the second task because of the different pictures constituting the problems being grouped in two scenes, but equivalent to the standard A:B::C:? task in other respects.

The materials of the last two tasks were based on materials previously used by Thibaut et al. (2011). The four trials of each task were two trials with weak association strengths between A and B, C and T, and C and Dis, and two with strong association strengths in order to equilibrate this factor.

The tasks were displayed on a Tobii T120 eye-tracker device with a 1024x768 screen resolution.

Procedure

Appropriate controls were carried out to ensure that the participants knew what the items in each of the problems were and that they understood the instructions. In the first task, they were asked to point to the element in the bottom scene that played the same role as the one which had an arrow pointing to it in the top scene. The two others tasks were administered as in Thibaut et al. (2011). Eye-tracking data was gathered from moment of the initial presentation of the problem to the moment a choice of one of the answers was made. The participant’s scanpath for a particular problem consisted of a record of his/her gaze-fixation points taken every 8ms.

Data Analysis

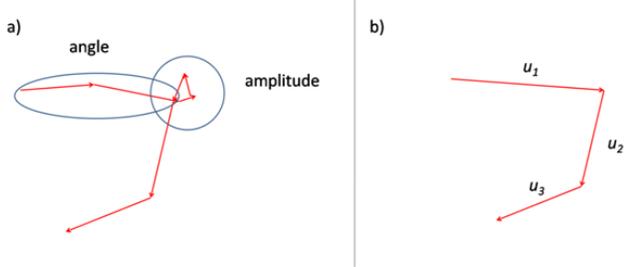


Figure 2. Simplification of a scanpath

The goal of this analysis is to compare the sets of children’s and adults’ scanpaths and to show that there are quantifiable differences in the two. To do this we use a combination of (a variant of) Jarodzka et al.’s (2010) scanpath-comparison algorithm, multidimensional scaling and a neural-net classifier. As the latter two techniques are well known, we will not discuss them at length. However, the Jarodzka et al. algorithm is relatively recent and requires explanation.

Jarodzka et al. (2010) scanpath-comparison algorithm

The algorithm is designed to determine the similarity of any two scanpaths. It consists of two phases, a simplification

phase and a comparison phase. A scanpath is considered to be made up of a series of “saccade vectors,” i.e., a connected series of vectors whose endpoints correspond to coordinates of successive gaze points (Figure 2a). First, the scanpath is simplified by combining into a single vector two consecutive saccade vectors if:

- i) their combined length does not exceed 200 pixels in amplitude (i.e., each is very small) and
- ii) they are nearly in straight line (i.e., the angle between them is between 2.62 and 3.67rad).

In other words if a saccade vector is very small or very linear with respect to its predecessor in the scanpath, the two vectors are combined (Figure 2b).

Once each of the two scanpaths has been simplified, they can be compared. We begin by giving an intuitive explanation of how this is done. Assume, for example, there are two simplified scanpaths, S_1 and S_2 made up of 3 and 4 saccade vectors, respectively. In other words, $S_1 = \{u_1, u_2, u_3\}$ and $S_2 = \{v_1, v_2, v_3, v_4\}$. Note that these saccade

a)

	v_1	v_2	v_3	v_4
u_1	$\Delta(u_1, v_1)$	$\Delta(u_1, v_2)$	$\Delta(u_1, v_3)$	$\Delta(u_1, v_4)$
u_2	$\Delta(u_2, v_1)$	$\Delta(u_2, v_2)$	$\Delta(u_2, v_3)$	$\Delta(u_2, v_4)$
u_3	$\Delta(u_3, v_1)$	$\Delta(u_3, v_2)$	$\Delta(u_3, v_3)$	$\Delta(u_3, v_4)$

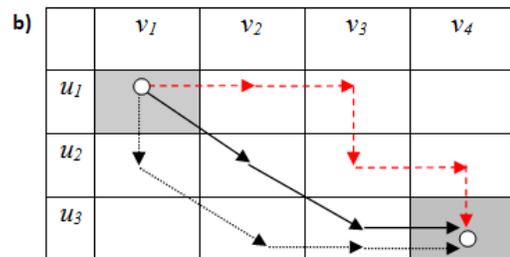


Figure 3. Saccade-vector difference table (a): Each of the saccade vectors from each of the two scanpaths are compared based on the chosen metric. (b) The comparison of each pair of stretched scanpaths corresponds to a traverse of the table from the upper-left to the lower-right corner of the saccade-vector difference matrix (the only directions of movement permitted are down, right and diagonally down-and-right). We find the path that produces the lowest total difference value and this value is the similarity measure assigned to S_1 and S_2

vectors are ordered in time. For example, in S_1 , the saccade vector u_1 is followed by u_2 , which is followed by u_3 . To compare S_1 and S_2 , we need two scanpaths of the same length. To achieve this, we will "stretch" each scanpath by adding immediate repetitions of saccade vectors, so that

they both have the same length. Our goal is to find the two stretched scanpaths, SS_1 and SS_2 that are as similar as possible with respect to the chosen metric (orientation, length, etc.). This similarity will be the measure of the distance between S_1 and S_2 .

The easiest way to illustrate this stretching is by means of a saccade-vector difference table for the two scanpaths, S_1 and S_2 , defined above.

A saccade-vector difference matrix is first created (Figure 3a). Each of the saccade-vectors making up one of the scanpaths S_1 is compared to each of the saccade-vectors of the other scanpath S_2 , according to a metric, generally, vector magnitude or orientation (length in our study). Once this table is constructed, we consider all paths through the table that begin with the comparison of the first saccade vectors in both scanpaths (i.e., cell (1, 1) of the table, $\Delta(u_1, v_1)$) and end with a comparison of the final saccade vectors in each scanpath (i.e., cell (3, 4) of the table, $\Delta(u_3, v_4)$) and always move to the right, down, or diagonally down-and-right. Three examples of paths through the matrix are illustrated in the right-hand panel of Figure 3. Each path through the table corresponds to the comparison of two specific stretched scanpaths. For example, the uppermost path shown corresponds to a comparison between $SS_1 = \{u_1, u_1, u_2, u_2, u_3\}$ and $SS_2 = \{v_1, v_2, v_3, v_3, v_4, v_4\}$. This path corresponds to the sum of the values in the cells (1,1), (1,2), (1,3), (2,3), (2,4), (3,4) of the saccade-vector difference matrix. When all of these paths through the matrix are considered, the path which has the smallest value (i.e. the smallest cumulative sum of comparisons) is selected. This path corresponds to the two stretched scanpaths that are the most similar. This value, normalized by the number of comparisons done, is the similarity measure assigned to the comparison of scanpaths S_1 and S_2 .

Note that the algorithm as described here differs from Jarodzka et al. (2010) in that it does not rely on the more complex Dijkstra (1959) tree-search algorithm. Instead, we constructed a matrix, cell by cell, with the lowest cumulative sum of comparisons possible for each cell while taking into account the constraints put on the comparisons of the two scanpaths (navigate rightward, downward, or diagonally downward and to the right). In our example, the final distance value between S_1 and S_2 is the cumulative sum in C(3,4) normalized by the number of steps taken through the matrix. This algorithm was computationally less complex for identical results.

The Jarodzka et al. (2010)/MDS/MLP algorithm applied to scanpaths of analogy problems

We only compared the scanpaths from strictly identical problems, but not different trials from the same task. Thus, when we were comparing an adult scanpath and a child's scanpath, the disposition of the items in the problem they were solving was identical.

In this way, for a given set of isomorphic problems (i.e., where all of the items were in identical places on the screen), we computed the differences between all pairs of scanpaths. In other words, if there were S_1 to S_n scanpaths from children and A_1 to A_m scanpaths from adults on the same set of isomorphic problems, we computed the similarity of all pairwise comparisons of scanpaths S_i versus S_j , S_i versus A_j , and A_i versus A_j for all i and j .

Once we had calculated the mean differences between scanpaths generated by each participant in each task, we used Multidimensional Scaling to obtain the coordinates on a 2D map that best preserved the distance between scanpaths. As can be seen in Figure 4, for each of the three tasks, the scanpaths clustered according to participant type (Adult or Children). We verified this clustering using a 3-layered perceptron (MLP) with a bias node on the input and hidden layers (5 hidden units, learning rate = 0.05, momentum = 0.9) with the coordinates of each scanpath on the MDS map translated into bipolar values and concatenated on input. We used a Leave-One-Out cross-validation technique to test the robustness of the classification. Leave-One-Out cross-validation is a standard technique in machine learning whereby the classifier (in this case a neural network) is trained on all items but one. Once training is complete, the classifier is tested on the item that had been left out to see whether or not it is classified correctly.

Results

Using the method of analysis described above, we did a pairwise comparison of all scanpaths generated by adults and children on isomorphic analogy problems. We then conducted a multi-dimensional scaling analysis of this data, which produced the location-map clusters shown in Figure 4. These points are a 2D representation that best reflects the distances between the scanpaths. The crosses correspond to children's scanpaths; the circles correspond to adults' scanpaths.

Classification of adults' versus children's scanpaths

The Jarodzka et al. (2010) method along with Multidimensional Scaling led to a 2D location map that best represented the relative distances between the set of scanpaths, as calculated by the Jarodzka et al. algorithm (Figure 4). A three-layered feedforward backpropagation network (MLP) with a Leave-One-Out cross-validation method, was used to test the robustness of a classification of the points representing the two groups (i.e. children and adults). For the scene analogy and A:B::C:? tasks (Figure 1a and 1b), the network classified 74% of the participants correctly based on their scanpath (70% of the 20 adults and 78% of the 23 children for both tasks). For the real-world A:B::C:? task, the network classified 72% of the subjects correctly (65% of the adults and 78% of the children). This

was significantly above chance (50%) for each task (binomial test: $Z=14.89$; $p<.001$ for the first and second; $Z=14.30$; $p<.001$ for the third). Intuitively, this result can be

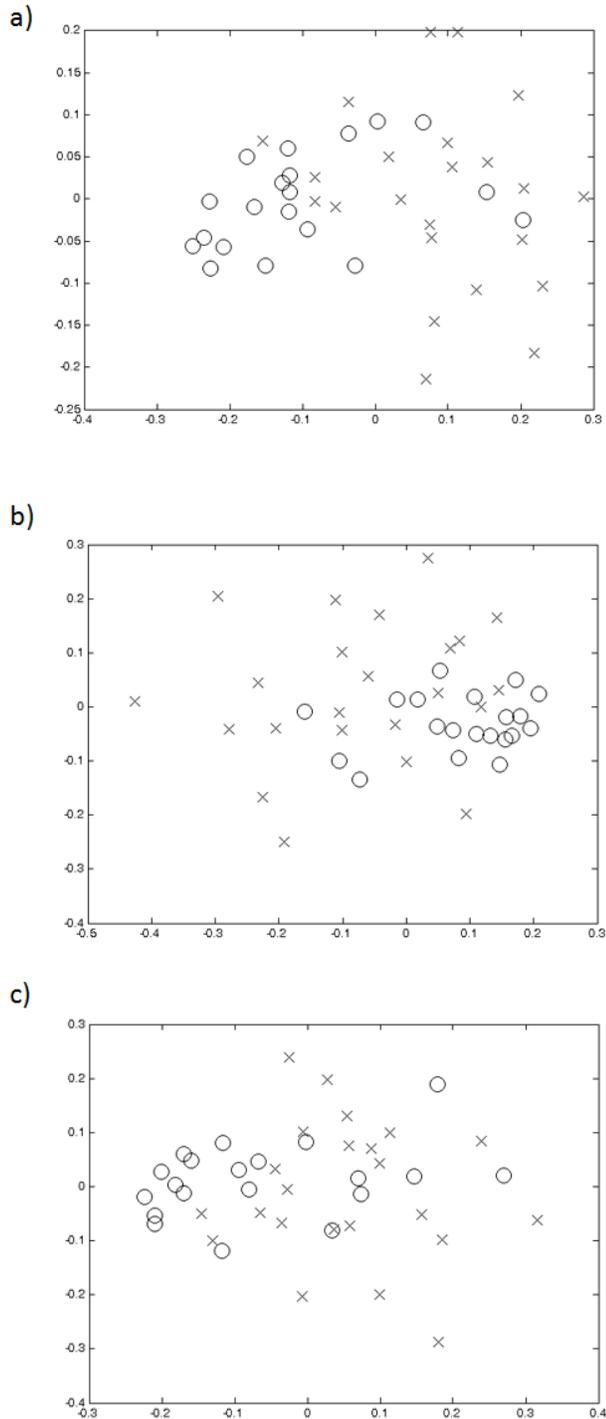


Figure 4. Location-map of an MDS analysis of the relative differences among participants for the scene analogy task (a), the standard A:B::C:? task (b), and the scene-oriented A:B::C:? task (c). Crosses represent children's scanpaths; o's are adults' scanpaths.

seen in Figure 3. The adult group tends to be more homogenous than the children as the crosses (children's scanpaths) are more scattered than the circles (adults' scanpaths), and this is reflected in the high degree of accurate classification of the MLP.

General discussion

The present study addressed the following question in a novel manner: Do children and adults have different visual strategies in analogical reasoning tasks? To answer this, we used an eye-tracking methodology whose data were analyzed by a combination of the Jarodzka et al. (2010) scanpath-comparison algorithm, the transformation of this data into a 2D location map using multidimensional scaling, and, finally, a quantitative adult/child classification by means of a feedforward backpropagation network. The neural-net classification was done by training the network on the scanpath data for all but one participant. Once the network was trained, it was tested on the one scanpath that was left out of the training set. This was done for each participant's scanpath data and the result was scored according to whether the network classified the test scanpath correctly or not. The results obtained with this method agree with previous results from Thibaut et al. 2011 who also showed, by analyzing item gaze times and the number of transitions between items that adults and children differed in their search strategies in the standard A:B::C:? analogy task. The present work, using an approach based on individuals' entire scanpaths, also extends this previous work to scene analogy problems and scene-oriented A:B::C:? problems. This scanpath analysis showed, among other things, that children's scanpaths were more variable than those of adults in the three tasks. These differences support the hypothesis of the key role of executive functions in analogy making because the lower variability of adults' scanpaths is indicative of them applying, through control of attention, a previously adopted plan for solving analogy problems (Woods et al., 2013)

The scanpath analysis presented in this paper provides a means of studying various search strategies in analogy making. The technique presented in this paper overcomes thorny problem of comparison of scanpaths of different lengths and allows to take into account the dynamic features of search, which are largely missed in other, more static eye-tracking approaches based on item fixation times. It could also be used, for example, to confirm differences in analogy-making strategies observed in adults in Bethell-Fox et al. (1984) and to classify participants based on their scanpath data (i.e., "elimination strategies" for participants with low fluid intelligence and "constructive matching strategies" for participants with high fluid intelligence). This method is, of course, not limited to studies of analogy-making, and could be used with any other type of problems

whose crucial information for its solution could be presented on a screen.

Conclusion

The method of scanpath analysis presented in this paper provides a new tool to analyze the dynamic aspects of search strategies in a wide variety of experimental contexts. As shown by the results, this method is sensitive to global differences between scanpaths and is useful to discriminate clusters of strategies. In this paper it has been used to show that children's and adults' differ in their variability while solving analogical reasoning problems, suggesting the involvement of executive functions in such tasks. However, to fully understand the causes of these differences, it is inevitable to use local information. Thus, it should be used in combination of other existing methods, in particular, Area-of-Interest (AOI) methods that provide information on *what* information is sought and how long it is watched (informativeness of stimuli), since this information is not captured by the Jarodzka et al. method. On the other hand, AOI methods give limited information about the dynamic progression of search, something which is captured when full scanpath information is used. In short, the Jarodzka et al. (2010), combined with an MDS analysis and a classifier (backpropagation networks, Support Vector Machines, etc.), provides a potentially far-reaching tool for analyzing participants' dynamic strategies in various problem-solving contexts.

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