Modeling Diagrammatic Reasoning: Route Planning on Maps

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Abstract:

Diagrammatic reasoning, reasoning from graphical representations rather than from word-based representations, is of particular importance for the military. Maps, pervasive in the military, are specific instances of diagrams that are used to provide current and projected information. Military maps are used for mission planning and increasingly for real-time situation awareness updates. Diagrams can offer "cognitive shortcuts" relative to verbal descriptions of certain kinds of information, notably relational and spatial information. Thus, diagrams reduce the working memory load and make possible certain cognitive efficiencies. However, for more complicated maps or maps that change over time, users may have difficulty extracting all relevant information or fail to notice changes in the map.

We are investigating the relationship (and dependencies) between perception and reasoning during a problem solving task that utilizes a diagram. The goal of this research project is to produce cognitively congruent models of a diagrammatic reasoning task. We collected data from human participants performing two simple tasks on a 5x5 grid-based map. Grid-based maps consist of labeled points, lines, and regions. The simplicity of these maps allows us to isolate the effect of specific changes in the maps and extract rich cognitive data. Specifically, the two tasks consist of either searching for a target location (perception) on the map or planning a route from a starting location to the target location and executing that plan (perception and decision making). Using these data, we have constructed a human cognitive model performing these same tasks. The data suggest several hypotheses, which will be examined in a future study on route planning using a more complex and realistic graphical maps modeled after subway maps.

1. Introduction:

Diagrams can be used to facilitate the reasoning and problem solving. Diagrams store information, provide cognitive efficiencies, and organize information. During the problem solving process, a diagram can be modified or manipulated to illustrate the current problem state. The process of using a diagram to assist the reasoning process is referred to as diagrammatic reasoning. The study of diagrammatic reasoning has a basis in perceptual psychology, cognitive modeling, artificial intelligence and mathematics. Many mathematical problems use diagrams during the problem solving process; combining problems based on graph theory and other mathematics with an understanding of perceptual psychology enables us to design quantitative experiments that establish a rich understanding of diagrammatic reasoning.

In our context, a diagram is a planar representation consisting of points, lines, regions, and other graphical elements. Diagrams encompass a wide range of complexity and include maps, geometric figures, and free body diagrams as shown in Figure 1.

Figure 1: Diagrams used in different types of problem solving.

Maps illustrate this range of complexity and provide an environment for wide array of diagrammatic reasoning tasks. In its simplest form, a map may merely be a line with labeled points (rail or subway maps). A more complex map may incorporate information about terrain features, roads, and specific locations and contain a legend. These maps consist of simple geometric figures augmented by symbols, icons, and colors. The shape of an airplane may represent an airport while a cross hatched line represents a railroad. Color further augments this information, a blue line may represent a river (and be easily ignored) while a bold red line may represent a major road (and readily attract attention).

During diagrammatic reasoning, information is obtained directly from the diagram through visual perception. The structure of the diagram gives an organizational structure to the information. For example, if you search for and find an airport on a map then the roads leading to the airport are connected to symbol for the airport. In a text-based description of geospatial information, the text would have to specifically list each relationship indicated on the map, such as “left of,” “to the north,” “10K from,” etc. This information would have to “re-assembled” via either a mental or physical map (both methods being time-consuming and error-prone) before the information could be used. Essentially, the user would have to reconstruct the map in order to use the information. The diagram can also be manipulated either physically or mentally to reflect the current problem state. For example, in route planning, map-users frequently keep track of the roads by highlighting the route.

Two common military examples of problem solving involve maps: route planning and situational awareness updating. Maps are diagrammatic abstractions of geospatial information, and display this information more efficiently than textual or verbal descriptions. A text-based description of geospatial information would have to explicitly list each relationship displayed in the map. In fact, diagrammatic reasoning may be essential to certain types of problem solving, including route planning. However, we do not understand precisely how perception and cognitive problem solving interact during the diagrammatic reasoning process. How does the nature of a problem solving task affect the interaction between visual perception and reasoning? What is the time course of the perceptual and the problem solving processes; are they sequential or parallel? The diagram may be used as a form or short term memory, or a mental image of the diagram may be held and constructed in the mind. The diagram may also provide cognitive efficiencies, allowing users to bypass formal, logical arguments or deductions.

We have conducted an experiment on target search and route planning and built a cognitive model of these tasks in order to investigate diagrammatic reasoning. In a model-test-model paradigm, cognitive models of route planning were initially used to investigate heuristic approaches to the task, and then to design an experiment that quantifies the search and route planning tasks in a meaningful way. The initial model was then adjusted based on experimental results. Using a computational approach to design the experiment and then building a cognitive model based on the experimental results has two benefits: It advances our understanding of the human process of diagrammatic reasoning and lays the foundations for an efficient, robust, and cognitively congruent method of automated reasoning.

The cognitive architecture, Adaptive Control of Thought- Rational (ACT-R) [1], [2] can be used to model diagrammatic reasoning – the perceptual process of obtaining information from the diagram and the problem solving process of interpreting the relationships. The ACT-R cognitive architecture is well developed with respect to memory, learning, and problem solving. The aspects of the architecture that involve the perceptual process are less well developed; currently visual search and attention can be directed by heuristic procedures but not the individual perception per se. For example, the architecture can not simulate saccades or the effect of distractions outside the model.

Specifically, we have applied research on visual search (based on quantitative data), qualitative research on diagrammatic reasoning, and graph theory [3] to our study of route planning. We designed a study of diagrammatic reasoning by using cognitive modeling to determine relevant variables and possible reasoning strategies. We used this information to construct a quantitative record of a task involving diagrammatic reasoning. Using the quantitative results, we then constructed an objective representation of route planning and search tasks on a grid-based map.

Route planning can be divided into two tasks: finding the starting and destination locations and planning the route. These tasks actually consist of numerous subtasks such as: identifying these locations, deciding where to start the visual search, how to proceed during the visual search, deciding on a route planning strategy: taking a global strategy (using all available information) or taking a hill climbing strategy that utilizes only local information. The user may have to recognize obstacles or problems with path; retracing back to a decision point along the route or returning to the starting point. The user may have to make a variety of

tradeoffs regarding speed and other “cost factors” such as the dollar cost of a toll or being at risk due to dangerous conditions. Collecting this information is particularly difficult because people may not be aware of these decisions and can not articulate this process. Other issues include the effect of the complexity of the diagram on memory load and strategy, and dual tasking. Diagrammatic reasoning requires two disparate tasks to be maintained simultaneously: visual perception and reasoning related to the problem solving process. There are also issues involving expert and non-expert performance in diagrammatic reasoning. In some contexts, the use of a diagram seems almost automatic, but other types of diagrammatic reasoning may require specific experiences or prior knowledge. For example, in geometric problem solving, experts can anticipate the problem from the diagrammatic information provided.

We can apply the results of our research on two different levels. We would like to understand the optimal placement and combination of diagrams and text for learning and long-term retention. That is, it may be possible to build a more effective diagram simply by changing a small aspect of a diagram. We would also like to apply this research to the development of automated diagrammatic reasoning systems. In time critical situations, an automated reasoning system would present possible courses of action based on diagrammatic information.

2. Literature Review

This research project incorporates psychological research on target search, research on cognitive modeling in the ACT-R theory and language, and mathematical research on graph theory. We review sources which have a significant influence on the development of the project.

Treisman and Gelade [15] examined how the integration of visual features influence a viewer’s attention on a visual scene. Attention is directly serially to features such as color, orientation, and spatial frequency. For example, if the target is distinguished by a unique feature (a red “X” in a field of blue “Xs”), then it essentially “pops out” with no conscious attention. However, if the target has features that overlap with other items (a red “X” in a field of red “Os” and blue “Xs”), then the conscious attention will need to be directed to individual items on-at-a-time until the target is located. Thus, in a scene with more potentially distracting features and with greater spatial frequency, visual searches take longer and have a higher error rate. This suggests that the size and complexity of a grid-based map will affect the participant’s responses. Our goal is to develop a grid based map where the effect of distracting features and spatial frequency are minimized to control for background variance so that the perceptual and the reasoning process of interest can be isolated.

Trick and Ennis [16] discuss the pre-attentive process during a visual search task. This suggests that participant’s visual attention is not immediately engaged by the search task at the onset of the diagram. Instead, a participant may pre-attentively collect visual information such as colors, spatial density of the grid, and orientation before focusing their visual and cognitive attention on either the search or the planning task.

Folk, Remington, and Johnson [9] determined that providing guidance (visual priming) during the search task results in faster responses. They studied positional and color cues in this study, and also discovered that participants ignored erroneous cues. Fick and Byrne [8] used the quantitative results of this study to construct a cognitive model of this task. The procedure in this study reflects the goals of this project – to collect quantitative data on the task of route planning and build a cognitive model of the task.

Post-attentive vision is studied in Wolf, Klempen, and Dahlen [17]. This study suggests that information collected during the pre-attentive state is forgotten when visual is deployed elsewhere. To paraphrase this research: you know what your keys look like, you may "see" your keys during a visual search for another object, but afterwards you will not remember where specifically your keys are located since they were not the object of the search.

This suggests the following sequence of effects during the route planning task. At the onset of the map, visual perception pre-attentively gathers information about spatial density orientation, distracting features (such as missing edges) etc. This process takes a longer period of time if there are more distracting features present or, possibly, even if the diagram differs from the expected value. The participant then focuses attention on the subtasks involved in the route planning task. The pre-attentively gathered information may require additional inspection such that and visual attention may again be directed explicitly to the areas observed pre-attentively.

Cassenti and Kelly [5] demonstrated that there is some memory of feature information associated with distracter items, even in a pop-out search that does not require conscious attention. This suggests that in our task, participants will retain information obtained from the map during a search for the destination location, even if that information is not immediately relevant to the current subtask. For example, participants may remember that some expected edges are "missing" from the grid-based map, but not specific information about where the "missing" edges are located.

Bourke and Duncan [4] studied the effect of dual tasking on performance. They examined the effect of dual tasking. In their study, participants performed a target searches while simultaneously listening to a story. The participants remembered less information about the story if they conducted the target search while hearing the story at the same time than listening alone. Common elements in the tasks seem to further decrease performance and there may also be a conflict between the reasoning (required to direct these tasks) and visual and auditory perception. This suggests that, if finding the target and planning the route can be considered two separate tasks, then some dual tasking effects may apply. It may be that in planning a route, participants first locate the destination location, just like the search task alone. Simultaneously though, participants must also remember that this is only a subtask to the main task and they must also reason about path-related information, such as whether or not an edge (path) connects two locations. Thus to the degree that other subtasks of the route planning task overlap with the search subtask, performing the search subtask may be degraded in the route planning task relative to performing search alone.

With respect to diagrammatic reasoning literature, from a more theoretical viewpoint, Simon and Larkin [13] discuss how and why diagrams provide cognitive efficiencies. In a diagram, related information is grouped together and inferences can take place at a perceptual level. That is, it is not necessary to perform the mental equivalent of modus ponens, to conclude

that if "X" is related to "Y" by "g" and "Y" is related to "Z" by "g" then "X" is related to "Z". Diagrams are used extensively in situations where text-based representations would be extremely cumbersome. This suggests that in route planning, planners can exclude a quantity of information as irrelevant, such as the labels of locations intermediate to the initial and destination locations. The labels of the intermediate locations could not be discarded in a text-based description; they would be required to move from one relevant statement to the next.

Koedinger and Anderson [12] and McDougal et al. [14] addressed this issue in geometry theorem proving. They conclude that geometry experts skip steps while solving geometry problems. Koedinger and Anderson [12] constructed a heuristic model of geometry theorem proving. The researchers observe that problem solvers go through an adaptive process, and that a limited rule set and restricted situation assist users in becoming experts. The limited complexity of the grid-based maps suggests that our participant data will not reflect a division between experts and non-experts. We also avoid the possibility that some people "naturally" form and use this type of diagram while other people do not.

Research performed by Hegarty and Just [10] suggests that a person's ability or experience with diagrams do not diminish the diagram's value in terms of learning and retention. They demonstrated that student retention and understanding is increased by using both text and diagrams to illustrate educational material. Having both text and diagrams forces students to make referential links between the two types of information.

To develop efficient and tractable systems of diagrammatic representation and automated diagrammatic reasoning systems, two approaches to the study of diagrammatic reasoning must been considered: using theories and algorithms from artificial intelligence and studying human cognition. Chandrasekaran et al. [6], [7] have explored using techniques from artificial intelligence to construct an automated diagrammatic reasoning system. This diagrammatic reasoning system (DRS) is based on perceptual and action routines. Perceptual routines determine spatial relationships between the points, lines and edges in the diagram. The action routines modify the diagram in order to obtain inferences. The routines are based on computational algorithms that rigidly process information obtained from the diagram. For example, deciding if an n sided polygon is located inside an m-sided polygon required on the order of m X n computations. Effective automated reasoning systems may depend on either classical computational algorithms, heuristic algorithms based on human behavior, or some combination of these two approaches.

In this research we study human behavior - the interaction between visual perception and reasoning during problem solving using a diagram. Our goal is to produce a cognitively congruent model of a route planning task. The specifics of the task and map type draw heavily on the results of the research on target search and theories about reasoning and diagrams.

3. Methodology

Participants. The participants were 24 male students at the U. S. Military Academy between the ages of 18 and 23. All participants had normal or corrected normal vision since this is a

requirement for admission and retention at the Academy. As a pre-screening step, each participant completed a brief demographic questionnaire regarding sleep and recent injuries/illnesses. Next, the participants were provided with an overview of the study and given the opportunity to ask questions, express concerns, or ask for further clarification of the study during and following the overview. If they agreed to volunteer, each participant then signed a voluntary agreement affidavit. Participants received extra credit in their PL100 course (a freshman level psychology course) for participation.

Equipment. The experiment was conducted using E-Prime for both the presentation of the experimental display and for data collection of keystrokes and timing on a Windows-based computer with an extended keyboard (containing a numeric keypad) and mouse. The grid-based map was displayed on a 17 inch flat screen monitor with a resolution of 1280 x 1024 pixels. The participants were seated approximately 24 inches from the screen.

Figure 2 shows an example of the grid-based map display. The diagram was kept as simple as possible – uniform white lines and labels on a black background – to minimize the number of features in the diagram that could create a target pop-out (e.g., color) or otherwise distinguish the target destination. The resulting diagram is a grid of edges and locations with regularly positioned labels.

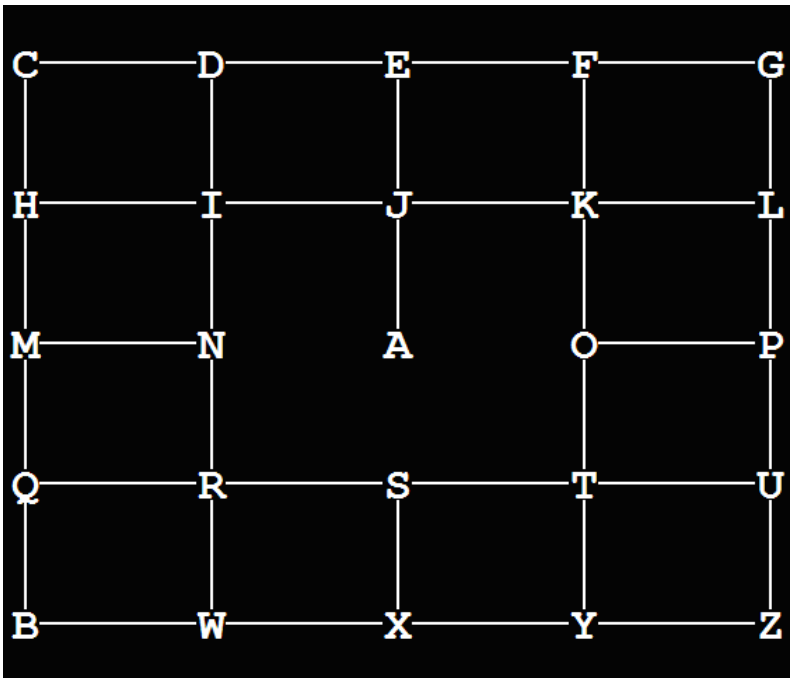

Figure 2: A screen shot of the grid-based map display showing the start point (A) in the center, the target or end point of the path (B) in the lower left corner, and two blocked paths leading from the center to B.

For both the search task and the route planning task, the start point (A) was in the center. The location of the end point (B) was varied randomly between trials such that across all trials it appeared in the four corners an equal number of times. Difficulty was varied by deleting either zero, one, or three paths (i.e. lines or grid edges) leading from a central location. Which of the four paths was deleted was determined by deleting paths in a counter-clockwise

manner such that in the one-path-deleted case, no further paths were deleted and in the three-paths-deleted case, the next two counter-clockwise paths were deleted. The leading edge (or the first path deleted) was distributed randomly and equally across trials. Thus the grid-based maps were varied by the variables: target location (4), leading edge (4), and the number deleted paths (3).When the number of paths deleted was crossed with the target location and leading edge, a new independent variable was created: the number of direct paths to the target that were blocked.

For example, in Figure 2, there are 3 deleted edges and the two direct paths to the target are blocked. The third deleted path does not block a direct route from the center to the target. In Figure 3, there are three deleted edges and but only one direct path to the target is blocked.

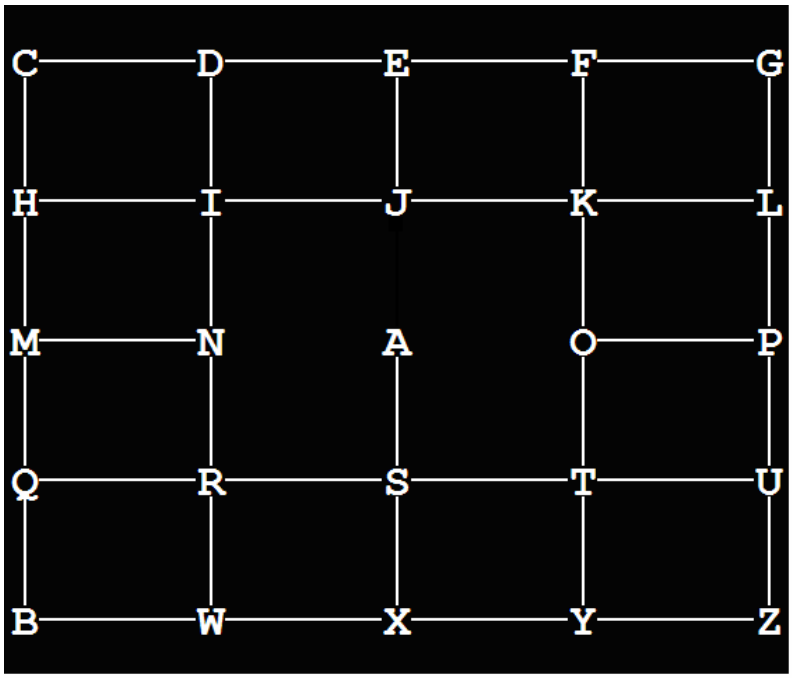

Figure 3: A screen shot of the grid-based map display showing the start point (A) in the center, the target or end point of the path (B) in the lower left corner, and one blocked path leading from the center to B

Experimental task. For the search task, participants were asked only to find the end point of the path, not a specific route they would travel to get there. When they located the target, they pressed the space bar. Then, to ensure that they actually had found it, they were presented with a grid with no letter labels and were asked to verify the location by using the mouse to designate the correct corner. For this task, participants were presented with the following instructions:

> *In this experiment, you will see a fixation point. Then you will be presented with a grid of letters. Locate the corner point marked with a B. When you have located it, press the space bar. The letters in the grid will then disappear and you will be asked to confirm the location of B by moving the mouse and clicking where B was located.*

After you respond, you will get feedback on whether you were correct and your response time.

Press the space bar to continue.

In the route planning task the participants were asked to use the arrow keys to plan a route, ending with the target. The participant used the arrow keys to move the red outline of a box along their proposed route. They pressed enter when they had completed the route and arrived at the target. In the route planning task, the participants were given the following instructions:

In this experiment, you will see a fixation point to start. Then you will be presented with a grid of letters. Locate the corner point marked with a B. Use the arrow keys to move the red cursor (which always starts in the center, marked with an A) over the B. When you are finished press Enter and you will get feedback on whether you were correct and your response time.

Press the space bar to continue.

The instructions were replaced by a blank screen with a fixation point for 1 second. This screen was then replaced with the grid-based map for both the search and route planning tasks. For the search task, after the space bar was pressed to indicate that the target was found, the labeled grid-based was replaced with an unlabeled one. The participants used the mouse to verify the target location. When the participants completed the mouse click then unlabeled map was replaced with a feedback screen. The feedback screen appeared for 1.5 seconds and indicated the response time and correctness. This screen was then replaced with a fixation point for 1 second. The participants were then presented with the next trial. In the route planning task, participants used the arrow keys in the numeric keypad to move the red cursor to the target location along the edges of the grid. The participants pressed the "Enter" key when they had completed this task. The grid was then replaced with a feedback screen for 1.5 seconds, which displayed the total response time and correctness. This screen was then replaced by a screen with a fixation point for 1 second. The participants were then presented with the next trial.

Experimental Design and Dependent Measures. The experimental displays were presented in six blocks of 48 trials each, where there were three blocks of each task type (search and route planning) and each block was balanced for the four target positions by the four leading edges. Each subject completed 3 blocks of each task type (search and planning), for a total of 288 trials. For the created variable of the number of paths blocked, each block of trials consisted of 24 trials with zero paths blocked, 16 trials had one path blocked, and 8 trials had two paths blocked. Out of the 16 trials with one direct path to the target blocked 8 had 3 paths from the center deleted. Of the 8 trials that had 2 direct paths blocked, all eight had three paths from the center deleted.

The analysis in this paper will be based on task type, target position, and the number of blocked paths. One-half the participants completed the search trials first, and the other half completed the route planning task. The experiment lasted approximately one hour, including the overview and briefing of the participants.

During the search task, we recorded the amount of time from the onset of the labeled grid-based map display to when the participant's pressed the space bar. The participants' accuracy was recorded, based on the identification via a mouse click of the correct target location on the unlabeled grid. During the route planning task, the amount of time from the onset of the labeled grid-based map to the first keystroke was recorded, as was the time and type of each subsequent keystroke until the "enter" key was pressed, indicating task completion.

Accuracy was determined by whether or not the red cursor was positioned over the target location when the "enter" key was pressed. The sum of these response times is the total response time. The red cursor would not traverse deleted or non-existent paths; however these keystrokes were recorded even though they did not move the box. These erroneous keystrokes were counted, as were multiple visits to the same location.

Results: Total Response Times

Subjects 1- 6 were removed from analysis, because, due to a programming error, accuracy was not recorded during the search task. For the remaining 18 participants, we filtered the search and route planning task data by accuracy, that is, if the correct target was not found then that trial was excluded from analysis. The first trial of each task type was excluded from analysis, since the response times were exceptionally long. In the route planning task, out of 2,592 individual trials, across all participants, only 51 trials were excluded. In the search task, out of 2,592 individual trials, across all participants, only 86 trials were excluded. The excluded trials were approximately evenly divided across all participants.

The mean response times for the search task (based on target position and the number of direct paths blocked) are shown in Figure 4. The mean response times (measured in milliseconds) for the route planning task (based on target position and the number of direct paths blocked) are shown in Figure 5.

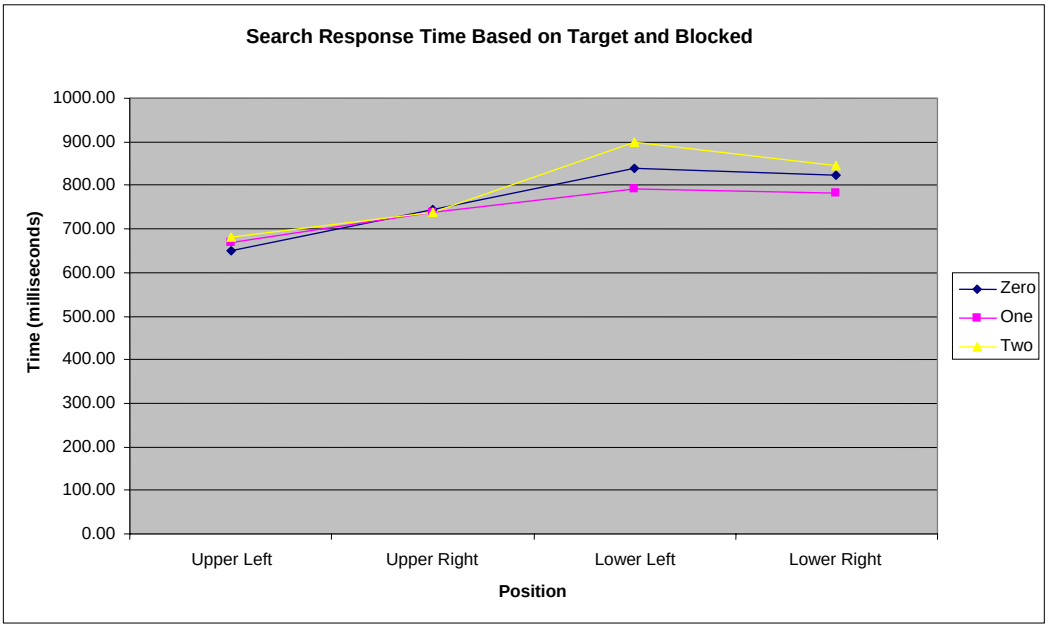

Figure 4: Response times for the search task.

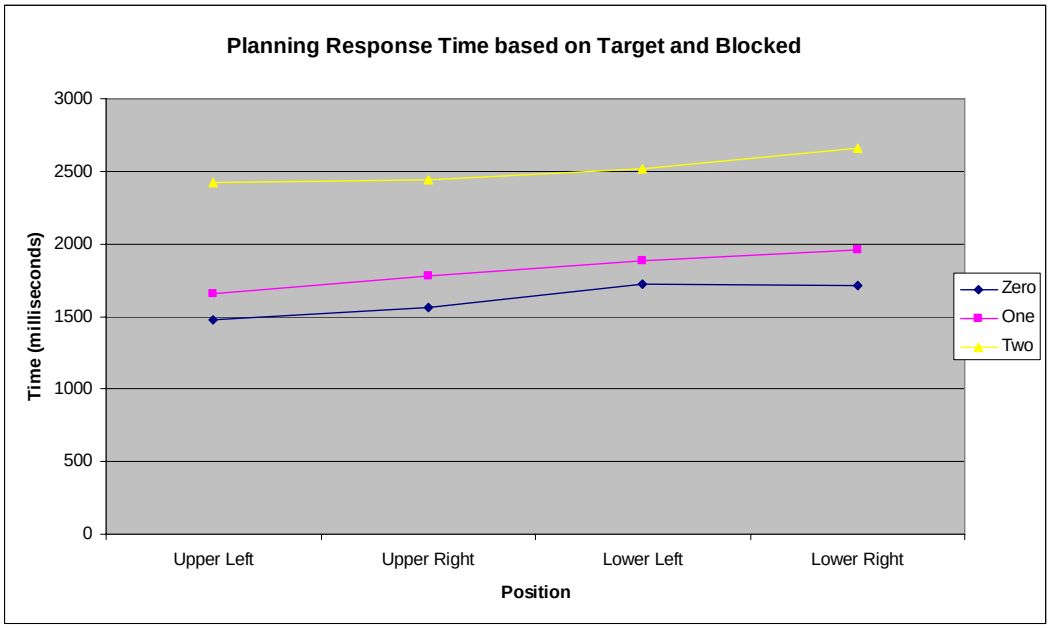

Figure 5: Response times for the route planning task.

The average completion time for the search task was 767.02 ms and 1983.64 ms for the route planning task. The difference between task types was significant, $(F(1,17) = 604.21, p < 0.001)$.

Collapsing across task type and the number of paths blocked, the average response time for targets in the upper left corner was 1259.78 ms, 1334.76 ms for targets in the upper right corner, 1442.04 ms for targets in the lower left corner, and 1464.73 ms for targets in the upper right corner. The target location was significant, $(F(3,51) = 27.52, \quad p > 0.001)$. Based on pair-wise comparisons, the difference between the upper left was significantly different from both the lower left and lower right with (p<0.001). The difference between a target in the upper right and the lower left was significant (p<0.002). The difference between a target in the upper right and the lower left was significant (p<0.001).

Collapsing across task type and target location, the average completion time for on a grid with zero direct paths blocked was 1191.486 ms, for a grid with one direct path blocked was 1283.069 ms, and a grid with two blocked direct paths was 1651.43 ms. The difference between any level of blocked was significant with $F(2,34) = 463.64, p > 0.001$.

The interaction between task type and blocked was significant, $(F(2,34) = 420.43, p > 0.001$. The average mean response time is shown in Table 1.
The interaction between task type and target was not significant.
The interaction between the variables: target and blocked was not significant. The interaction between the variables task type, target, and blocked was not significant.

	Route Planning	Search
Blocked: 0	1618.51	764.46
Blocked: 1	1820.64	745.50
Blocked: 2	2511.76	791.09

Table 1: Response time based on task and blocked.

Results: Response Time for the First Keystroke

The graph shown in Figure 6 depicts the average response times for the first keystroke in the planning task.

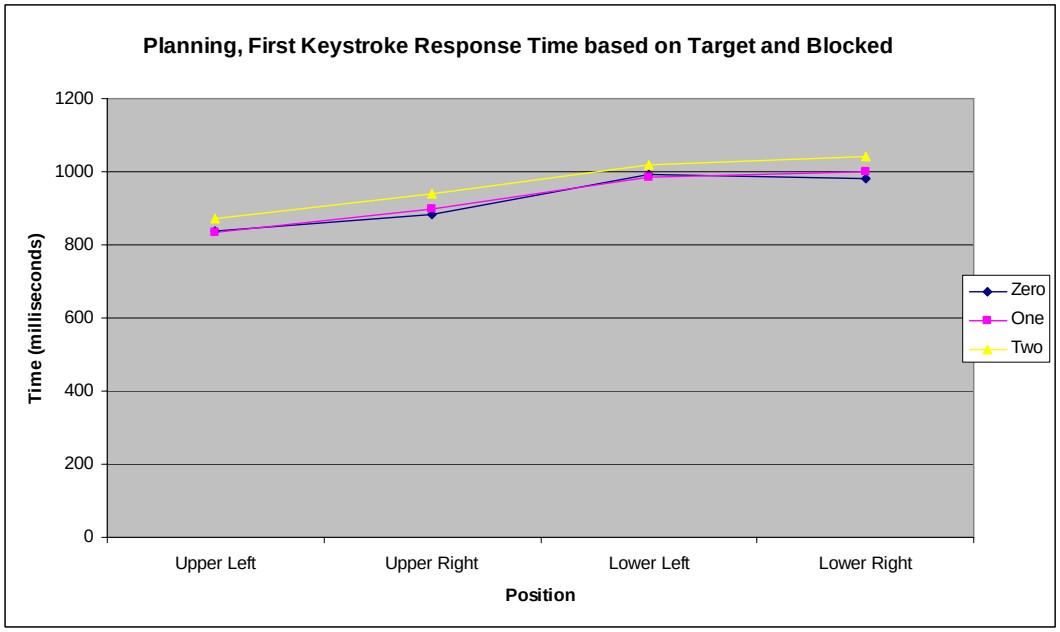

Figure 6: Response time for the first keystroke in the route planning task.

The mean response time for the first key stroke in the planning task was 940.23 ms and 767.02 ms in the search task. The difference between task types was significant, $(F(1,17) = 34.74,\ p > 0.001)$. The mean response time based on target was 757.15 ms for the upper left, 824.04 for the upper right, 920.87 ms for the lower left, and 912.44 ms for the lower right. This variable was significant with $(F(2,51) = 22.24,\ p > 0.001)$. The difference between targets in the upper left and the lower left was significant, $(p > 0.001)$, and the difference between a target in the upper left and lower right was significant $(p > 0.001)$. Similarly, the difference between a target in the upper right and targets in the lower left $(p > 0.004)$ and targets in the lower right $(p > 0.006)$. The mean response time for a grid with zero direct paths blocked was 843.92 ms, the mean response time for a grid with one direct path blocked was 837.30 ms, and the mean response time for grid with the two direct paths blocked was 879.65 ms. The blocked variable was significant, $(F(2,34) = 7.69,\ p > 0.002)$. The difference between zero and two blocked paths was significant with $p > 0.025$, as was the difference between one and two blocked path with $p > 0.004$. In this case, the interactions are not significant.

The mean response times for keystrokes 1-5 in the path planning task, based on blocked, are given the Figure 7.

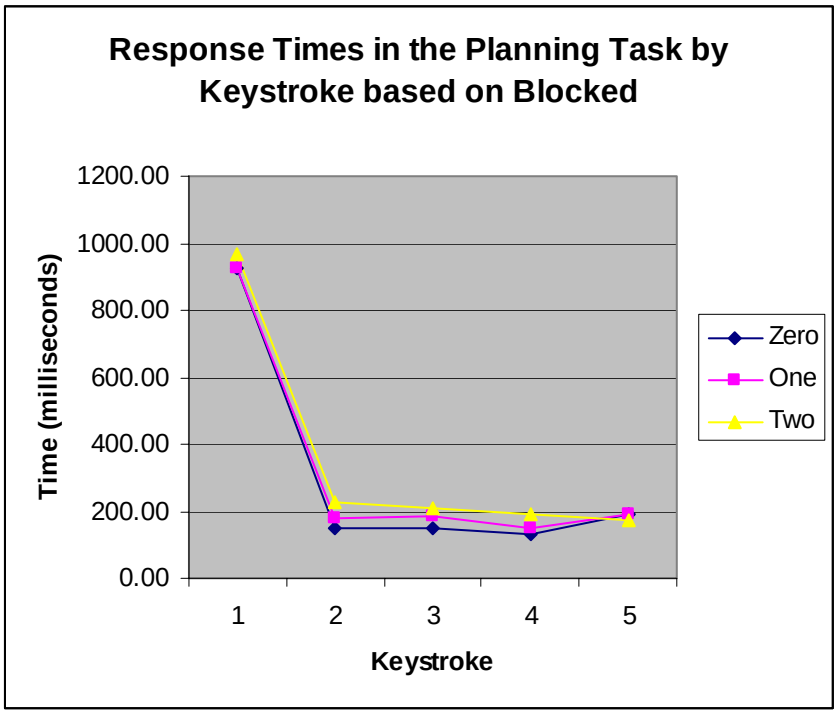

Figure 7: Response times for keystrokes 1-5 in the route planning task.

The mean number of attempts per trial to traverse a deleted (or non-existing) edge is recorded in blocked paths in shown in Table 2. The mean number of times a participant revisited a node per trial is recorded in back tracking in Table 2.

Subject	Mean: Back Tracking	Mean: Traverse a Non-existent Path
7	0.00	0.38
8	0.05	0.34
9	0.08	0.45
10	0.03	0.11
11	0.01	0.76
12	0.06	0.19
13	0.01	0.12
14	0.03	0.26
15	0.01	0.25
16	0.03	0.35
17	0.01	0.08
18	0.15	0.52
19	0.09	0.52
20	0.02	0.27
21	0.04	0.15
22	0.20	0.79
23	0.03	0.31
24	0.00	0.20

Table 2: Back tracking and traversing a non-existent edge.

4. Discussion

As suspected, completing the planning task requires greater time than completing the search task when comparing the total response time. This is also true when comparing just the response time for the first keystroke in the planning task with the search task. The greater mean response time for the first keystroke response time in the planning task suggests that choosing an initial direction for the route requires more cognitive processing than just identifying the target location.

For just the route planning task, the response times for the individual keystrokes suggest that the participants use a hill-climbing strategy to plan the path in the route planning task. The difference between the time required for the search task and the first keystroke in the route planning tasks is comparable to the time required for keystrokes 2-5 in the route planning task. (In the trials with zero and one blocked paths, a shortest path to the target location only requires 5 keystrokes.)

The experimental reaction time data examined by target location suggests that participants routinely search the diagram in a standard search pattern from left to right, top to bottom in both the search task and the route planning task. The effect of the target position is seen in the first keystroke response time for both tasks. The participants choose the next edge (or path) in their route by observing the edges connected to their current location on the route, but do not appear to read the location labels. (The response times are too fast to allow participants to both observe the connected edges and read the labels.)

In the search task, blocked paths have an effect on the response time in the search. This is true despite the fact that the blocked (deleted) paths have no relevance to the target position per se. The deleted paths also occur in the center of the diagram and are not near the corners, the potential target locations. This result was unexpected, but a possible explanation is that the change in the spatial frequency of the lines may pre-attentively distract participants, resulting in a higher mean response time. In the route planning task, the effect of blocked paths also persists beyond the first keystroke. The mean response time for keystrokes 2-5 in the case of two blocked paths is greater than in the case of one or zero blocked paths. We did not expect this result because the edges of the grid occur in a regular and predictable manner outside the center area of the grid. In some cases, the participants may have chosen a direction of travel based on the target position and only checked for blocked paths after pressing an arrow key to indicate a direction of travel.

The experimental results suggest that in both tasks the presence or absence of features and spatial frequency of the diagram display engage the participants' pre-attentive vision. The participants then engage in a serial search for the target location following a routine left-right/top-bottom search pattern that may be suggested either by the structure of the diagram or habits learned from reading.

In the route planning task, participants may experience post-attentive effects and recall that paths were deleted in the center of the diagram, but fail to recall the specific number or position of blocked (deleted) paths. This may account for the continued delay in keystroke responses in the two path blocked cases. In their responses, participants then seemed to

follow a strategy based on moving in a straight line (if possible) until the route reached the boundary of the grid, and then changing direction.

5. Cognitive Modeling

In the ACT-R modeling language (Adaptive Control of Thought – Rational), we have constructed cognitive models of the search and route planning tasks. The cognitive models first search the grid from upper left to upper right and then lower left to lower right until the model finds the target. In the model of the search task, the model then hits a key indicating that it has found the target location. The model of the route planning task builds on the search model. After finding the target, the model's perception focuses on the area around the starting location (A). The model's attention may be temporarily distracted by deleted edges. The model then selects the most direct, available path to the target location. The model then continues to choose arrow keys indicating the path of travel based on edges connected to the current location. The edges are selected based on two possible path building strategies: 1) select an edge that continues the route in a straight line or 2) choose an edge that brings the planner closer to the target location. If there is no straight line path that brings the model closer to the target destination (through a visual error or the straight path has reached the edge of the grid) then the model chooses an edge connected to the current location that approaches the target location.

There are some limits to the current model, even with some post-experiment adjustments. Currently, the model does not take account the type of errors where the participants attempted to traverse blocked paths. Also, consistent with the experimental results, but perhaps counterintuitive, the model does not read the labels of the intermediate locations on the route; the experimental results indicate that there is insufficient time for the model to focus on a label, read the letter, and decide if the label is "B."

Regarding strategy selection, the model selects the next edge in the route by focusing visual attention on the nearest edge in a region defined by the current location and the target location. In this way, the model plans a route that advances towards the target location. If possible, the model selects an edge that continues current direction. If no such edge exists, the model shift strategies and attempts to find an edge that advances the route towards the target position. The model does not revisit locations, since it does not makes errors when finding the target location.

The resulting models correlate with the search and route planning experimental data approximately 96-97%. This suggests that the models are a good fit in the case where no backtracking or blocked tries occur.

6. Conclusion

These results suggest several questions for future consideration. For example, the results suggest that a standard search path was followed by almost all participants in both the search and planning task. Changing the overall structure of the diagram will allow us to discover if the participants use a strategy based on reading patterns or if the diagram structure was the

primary influence on the serial search conducted by participants. We do not fully understand why the number of direct paths blocked continued to have an influence on response time. Structuring the route planning task to eliminate the possibility of different path lengths after the first keystroke will separate the influence of difficulty level (based on the number of changes in the direction of travel in a route) from path length. We would like to construct maps that encourage participants to choose a global planning strategy versus a hill climbing strategy based on local information. The choice of strategy could be influenced by assessing time penalties for directional changes in the route. Several participants mentioned using strategies from video game playing to accomplish the tasks as rapidly as possible after the trials. This suggests it would be valuable to include an exit interview about strategies. These interviews could be used to compare the recorded routes and times with the participants' route planning strategies.

A further enhancement to the route planning model being consider is to add variability with respect to which subtask executes first, search or the first part of the route planning. This kind of change would add additional model fit for the differences in first keystroke response times between pure search and search as part of planning.

We plan to analyze these questions in the context of "subway" maps. Subway maps are diagrams consisting of colored edges and labeled points or locations. Individual subway routes are assigned a color, and may be quite convoluted. This type of map will allow us to investigate all the questions specified above.

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