Classification and Identification of Heuristics Utilized In Table Comprehension through User Eye-Movement Analysis

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1. Introduction

With the tremendous increase in information availability, the use of graphical displays as a means of presenting quantitative information has become ubiquitous in everyday life. Effective design of these displays can aid in a wide variety of decision processes, from selecting a particular consumer product in a comparison table, to medical judgments of whether tissue is cancerous or healthy based on x-ray imaging. When making such decisions, decision makers often rely on the use of heuristics, effectively reducing a complex decision problem into simpler judgment operations (Tversky & Khaneman, 1974). While these heuristics are effective at reducing the cognitive effort required in a decision task, their use may also lead to systematic errors. The current project was designed in order to develop a set of tools to better investigate how the design of information displays (specifically tables) may influence the use of heuristics during a decision task.

1.1 Information Display Theory and Design

A large amount of previous research on information displays has focused on developing the human information processing theory underlying display comprehension and analysis. Pinker (1990) proposed a theory of graph comprehension that centered on perceptual and cognitive mechanisms. One interesting aspect of this theory is that it was used to make predictions of not only what designs would be effective, but also individual differences that make viewers better or worse at graph comprehension. Aside from theory development, other studies have examined specific mechanisms used in graph analysis and comprehension. For example, Ratwawni and colleagues (2008) performed a series of three experiments where participants were tasked with extracting and integrating information presented within population density graphs. Using eye movement and verbal protocol analysis the researchers developed a framework for a visual and cognitive information integration mechanism used in graph comprehension.

From the theoretical literature, several researchers have developed sets of guidelines to be used by practitioners to encourage efficient information display design (e.g. Bertin 1973, Wickens & Carswell, 1995). Kosslyn, S. (1989) suggests that designers can accomplish effective display design through a task analytic process. During this process the designer is to first identify four basic level graphic constituents
(i.e. background, framework, specifier and label). Each constituent is then assessed for adherence to certain acceptability principles. Recently, Tufte (1990, 2001) has produced several works created for designers, with numerous examples of both effective and ineffective display design categorized by specific design elements (e.g. layering and separation of data, small multiples, color, etc.). Although the previously discussed literature provides researchers and designers with valuable theory and direction for the development of information displays, the influence of display design on the use of decision strategies, or heuristics, by the viewer has been neglected.

1.2 Heuristic Identification

The identification of decision making heuristics and their associated systematic biases has maintained momentum during the four decades after the seminal work by Tversky and Khaneman (1974). Recently, Lee and colleagues (In press) have investigated how table design may influence heuristics utilized by decision makers when analyzing tabular data. In their study, participants were shown tables containing feature information for several different fictional television sets and were asked to make a decision as to which set they would purchase. Participants were presented with one of three table designs (see Figure 1) that differed on shading (horizontal, vertical, or none). The researchers proposed that horizontal shading was likely to induce the use of an “as-if” heuristic (AI) while horizontal shading would favor an “Elimination by Aspects” (EBA) heuristic (Tversky, 1972). These assumptions were based primarily on previous research in information access costs (Wickens & Carswell, 1995) and principles of Gestalt psychology. The primary task in the experiment was a free decision task, with participants self-reporting their decision strategy post-hoc. Results from the study trended toward an interaction of shading and heuristic used, but no significant results were achieved. In their conclusion, the authors indicate that analysis of viewers eye movements may allow for detection of changes in heuristic use during the decision making process. Outside of the author’s proposal of in-task heuristic switching assessment, we believe eye movements may allow for an active means of identifying decision heuristics while providing benefits over other methodologies.

The analysis of eye-movements and gaze patterns has received increased attention as access to eye-tracking systems becomes readily available, with researchers even presenting low-cost, self-made systems using over-the-counter hardware and open source software (Pavlas et al., 2011). While eye-tracking has a rich history in decision making research, the use of eye movement to understand decision making heuristics has been limited, taking a backseat to more traditional methodologies such as structural modeling and process tracing (Ford et al., 1989). We believe that eye movements may provide an additional opportunity for real-time monitoring of decision strategy, possibly even allowing for a DSS to present data applicable to the user’s current needs without any direct user input. However, before a study
to test these claims can be conducted, a set of tools must be developed to assist in the analysis of the complex eye-movement data. The following pilot study produced three main developments:

1. Collection of eye-movement data from three participants while utilizing a particular heuristic to make a decision given a table as an information display.

2. A set of tools for practitioners that analyzes collected eye-movement data and produces additional variables useful for the identification of cognitive heuristics.

3. A proposal of the potential components of a feature matrix that would be used for further forays into examining the classification problem with machine learning, along with a few learning methods that show promise.

2. Human Subject Data Collection Procedure

2.1 Participants

For the pilot study, three group members acted as participants. As the pilot is being performed to supply data, and not for inferential analysis, the participant’s knowledge of the study should not be an issue.

2.2 Materials

The primary stimulus materials were product comparison tables (see Figure 2 below). The left-most column of the tables contained generic product “names” (labeled Product 1 – Product 9) while the topmost row contained the products “features” (labeled Feature 1 – Feature 9). Tables were selected due to previous empirical studies demonstrating that they are effective displays in a variety of tasks (Meyer et al., 1997; Meyer et al., 1999), and their relative ease of manipulation. EyeWorks™ software suite
controlled the stimulus presentation, response recording and gaze tracking coordination.

<table>
<thead>
<tr>
<th>Feature1</th>
<th>Feature2</th>
<th>Feature3</th>
<th>Feature4</th>
<th>Feature5</th>
<th>Feature6</th>
<th>Feature7</th>
<th>Feature8</th>
<th>Feature9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product1</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Product2</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Product3</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Product4</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
</tr>
<tr>
<td>Product5</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
</tr>
<tr>
<td>Product6</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
</tr>
<tr>
<td>Product7</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
</tr>
<tr>
<td>Product8</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
</tr>
<tr>
<td>Product9</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
</tr>
</tbody>
</table>

Figure 2. Decision task stimulus

2.3 Procedure

Participants were instructed to select one product per table while relying on a particular decision heuristic (1 AI and 1 EBA) to determine which product is optimal. For the AI heuristic trial, participants were instructed to find the product with the most features. In the EBA trial, participants were provided names of three features that a product needed to have for it to be selected. Stimuli were generated so that only one response was appropriate while using a given heuristic. Participants indicated when a decision had been made by clicking on the product cell that met the heuristics criteria. There was no time limit on the decision. Prior to the presentation of each table, a white screen appeared with instructions for the following trial.

2.4 Outcome Data

The output from the data collection portion of the project can be found in the raw_data folder.

3. Detection and Characterization of Fixation

The input files were obtained from decision task and the fixations in the files were plotted and examined. Fixation is the region in the screen where the participant focuses their visual attention. Each fixation was characterized by centroid, weight and duration. Eye detector fixations were analyzed and clustered together according to spatial and temporal proximity. The fixations which had less than a stipulated number of detections were ignored. The slope between consecutive fixations was also
computed. Let $x, y$ and $t$ represent the spatial coordinates and the time instances of the detections. The spatial and temporal distance were calculated as:

$$d_{i,j} = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2}$$
$$t_{i,j} = |t_i - t_j|$$

Two detections $(x_i, y_i, t_i)$ and $(x_j, y_j, t_j)$ were grouped together if $d_{ij} < D$ and $t_{ij} < T$ where $D$ and $T$ are heuristically detected thresholds. Figure 3 illustrates the detections recorded over a period of time. Each significant fixation was marked by a circular frame. The fixations can occur on a specific cell, or at the borders or even outside the table.

![Figure 3: Illustration of fixation areas](image)

4. Feature definition

**Fixation weight:** The fixation weight is the number of detections present in one fixation and is represented by $N$.

**Fixation centroid:** The fixation centroid is the average of the detection points which can be calculated by:

$$x_c = \frac{1}{N} \sum_{n=1}^{N} x_n$$ and
\[ Y_c = \frac{1}{N} \sum_{n=1}^{N} y_n \]

where \( X_c, Y_c \) are the fixation centroid coordinates and \( x_n, y_n \) are the coordinates of each detection in the fixation.

**Fixation duration:** Fixation duration is the time interval between the first detection and the last detection in the fixation.

### 5. Table cell assignment

The screen area consists of area within and outside the table. The table area was again partitioned into cells which were the intersections of a product and a feature. The cell was assigned for each fixation lying within the table coordinates. Let the table area consists of \( P \times Q \) pixels and \( M, L \) be the number of the products and features respectively. The table area was equally partitioned to cells \( \frac{P}{M} \) pixels high and \( \frac{Q}{L} \) pixels wide. The cells were indexed by \( h = 1, 2, \ldots, P \) and \( g = 1, 2, 3, \ldots, Q \). The cell in which the centroid of a fixation falls, was assigned to that fixation. If the fixation centroid falls in the proximity of the border, the assignment is ambiguous. The cell assignment is depicted in figure 3.

![Figure 3: Illustration of cell assignment](image)

**Figure 4: Illustration of cell assignment**

In figure 4, if a fixation centroid falls in the hashed area, the cell assigned to that fixation is 1.5, 1.5. In general any fixation with its centroid within a distance \( R \) from the cell boundary was assigned the mean
cell number of the closest cells. Any fixation outside the table area was ignored. The slope between consecutive valid fixations was computed using their centroids.

5.1 Estimation of Spatial and Temporal Thresholds

The spatial threshold \((D)\) should be wide enough to incorporate gaze jitters but should be small enough so that the fixation area is not spread into multiple cells. Temporal Threshold \((T)\) should be big enough to tolerate any missed detections or eye blinks. A large \(T\) will combine multiple fixations. Both \(D\) and \(T\) was decided heuristically.

6. Algorithm:

Assumptions:

- **threshold distance (D):** the maximum distance between any two fixations in a cluster [20 pixels].
- **threshold time (T):** the maximum duration between any two fixations in a cluster [0.7 seconds].
- **ambiguousArea_X:** the distance from the cell boundary as a factor of cell width [0.15] considered as ambiguous or belonging to both cells.
- **ambiguousArea_Y:** the distance from the cell boundary as a factor of cell height [0.15] considered as ambiguous or belonging to both cells.

1. Read the Excel input file.
2. Extract the required columns from the file as it also contains nonessential data.
   The required columns:
   - x coordinate of the fixation
   - y coordinate of the fixation
   - Start time of looking at that fixation
   - Stop time of looking at that fixation
   - Duration in seconds (stop time - start time)
   - Number of samples in that fixation
3. Get the region coordinates of the table.
4. Compute the x and y coordinates of data region, product region and feature region.
5. Compute the width and height of cells in data region, feature region and product region.

   \[
   \text{DataCell.width} = \frac{\text{DataRegion.width}}{\text{numberofFeatures}} \\
   \text{DataCell.height} = \frac{\text{DataRegion.height}}{\text{numberofProducts}} \\
   \text{FeatureCell.width} = \frac{\text{FeatureRegion.width}}{\text{numberofFeatures}} \\
   \text{FeatureCell.height} = \text{FeatureRegion.height} \\
   \text{ProductCell.width} = \text{ProductRegion.width} \\
   \text{ProductCell.height} = \frac{\text{ProductRegion.height}}{\text{numberofProducts}}
   \]

6. Assign 1 to the cluster index.

7. Assign the value of cluster index to the current fixation.

8. Compute the distance between the coordinates of the current fixation with the coordinates of the next fixation.

9. Compute the difference between stop time of the current fixation and start time of the next fixation.

10. If the computed distance is greater than the threshold distance and the computed time is greater than the threshold time, increment the value of the cluster.

11. Repeat steps from 7 to 10 until all the fixations are assigned a cluster index.

12. Classify the coordinates according to their cluster index.

13. Those fixation whose cluster index is same, are grouped together.

14. The centroid of each cluster is calculated by:

   \[
   \text{centroid}_i(X) = \frac{\text{Mean}(x_1, \ldots, x_n)}{} \\
   \text{centroid}_i(Y) = \frac{\text{Mean}(y_1, \ldots, y_n)}{} \\
   \text{centroid}_i(\text{duration}) = \frac{\text{Max}(\text{StopTime}_1, \ldots, \text{StopTime}_n) - \text{Min}(\text{StartTime}_1, \ldots, \text{StartTime}_n)}{} \\
   \text{centroid}_i(\text{weight}) = \frac{\text{Sum}(\text{value(NumberOfSamples}_1, \ldots, \text{NumberOfSamples}_n))}{}
   \]

15. Compute the slope between every two consecutive clusters.

16. For every cluster (centroid), we assign the feature number and product number in which it falls:

   \[
   \text{centroid(FeatureNumber)} = \frac{\text{centroid}(X) - \text{Region}(X)}{\text{cell.width}} \\
   \text{centroid(ProductNumber)} = \frac{\text{centroids}(Y) - \text{Region}(Y)}{\text{cell.height}}
   \]

17. For every cluster, we determine whether it falls in the ambiguous area or not through steps 17 to 21:

   \[
   \text{distanceFromBoundary} = \text{round(centroid)-centroid}
   \]
18. For all centroid \( i \) whose \( \text{distFromBoundary}(X) < \text{ambiguousArea}_X \), its in the ambiguous area
\[
\text{centroid}_i(\text{FeatureNumber}) = \text{round} \left( \text{centroid}_i(\text{featureNumber}) + 0.5 \right)
\]

19. For all centroid \( i \) whose \( \text{distFromBoundary}(Y) < \text{ambiguousArea}_Y \), its in the ambiguous area
\[
\text{centroid}_i(\text{ProductNumber}) = \text{round} \left( \text{centroid}_i(\text{ProductNumber}) + 0.5 \right)
\]

20. For all centroid \( i \) whose \( \text{distFromBoundary}(X) > \text{ambiguousArea}_X \)
\[
\text{centroid}_i(\text{FeatureNumber}) = \text{ceil} \left( \text{centroid}_i(\text{featureNumber}) \right)
\]

21. For all centroid \( i \) whose \( \text{distFromBoundary}(Y) > \text{ambiguousArea}_Y \)
\[
\text{centroid}_i(\text{ProductNumber}) = \text{ceil} \left( \text{centroid}_i(\text{ProductNumber}) \right)
\]

Figure 5: The output of clustering; each cluster assigned a Feature Number and a Product Number

7. Methods of Heuristic Identification

The parsed datasets were labeled by heuristic and the subject’s name, allowing us to statistically analyze the datasets for any possible methods of heuristic identification. These datasets contained the coordinates of a fixation centroid in Cartesian space, the duration of the fixations in milliseconds, the number of
samples taken within each clustered fixation, the specific cell that the subject focused on, the slope of the line connecting two subsequent fixations, and the distance between two subsequent fixations. Assuming that we take this as our feature vector, we expect to use common machine learning algorithms to produce a label of “As-if” or “Elimination by Aspect” as output.

7.1 Feature Selection

The first step in determining if a pattern in the heuristics exists is feature selection; given the set of features collected from the raw data, we want to build a matrix of features, choosing only the features that are the most relevant to the output of our target function. A quick examination of the data shows that the slope and distance can be easily determined from the centroid coordinates, meaning that we can phase these values out of our feature matrix. Further, the duration and number of samples per fixation are closely correlated, as suggested by the eye tracker’s functionality. Finally, the identification for the cell on which the subject is fixated is not useful for our purposes, ad-hoc for the table being studied. Thus, our feature matrix will contain the centroid coordinates and the duration of fixation in milliseconds. As already explained, we will make use of the slopes and distances between subsequent fixation points, but these can be calculated from the centroid coordinates.

We also notice that the total elapsed time and total number of fixation points for a user attempting the as-if heuristic (AI) are, for two of our three subjects, less than those same values for a user attempting the elimination-by-aspect heuristic (EBA), as demonstrated in Table 1. Given our small set of subjects, we cannot accurately determine the mean or median quantity of fixation points for each heuristic. This can be rectified by taking additional samples of data for further analysis.

Second, we attempted a comparison of the length of eye movements, especially looking at the average magnitude for each heuristic. While this value does not affect our target function, we found that the average magnitude tends to depend more on the tested individual, not necessarily the heuristic being used. We then tried to compare the fixation durations across both heuristics, grouping the fixation clusters into blocks and taking both average duration and maximum duration across each block as our plotted value. With this data, we produced the plots shown in Figure 6.
<table>
<thead>
<tr>
<th>Heuristic Used</th>
<th>As-if</th>
<th>Elimination</th>
</tr>
</thead>
<tbody>
<tr>
<td>Will</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Samples</td>
<td>23</td>
<td>68</td>
</tr>
<tr>
<td>Durations</td>
<td>4.616</td>
<td>21.994</td>
</tr>
<tr>
<td>Remya</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Samples</td>
<td>30</td>
<td>21</td>
</tr>
<tr>
<td>Durations</td>
<td>7.234</td>
<td>5.017</td>
</tr>
<tr>
<td>Golnar</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Samples</td>
<td>18</td>
<td>26</td>
</tr>
<tr>
<td>Durations</td>
<td>4.465</td>
<td>7.564</td>
</tr>
</tbody>
</table>

Table 1: Number of samples taken at a fixation and the duration of fixation (ms) for each heuristic and subject.

Figure 6: Plots of normalized and maximized durations for both heuristics for the left eye.
The plots in Figure 6 show maximized and averaged plot points for each block for both heuristics evaluated with the left eye. We chose the left eye because it exhibited better data. The plots show no apparent target polynomial that could be used as a classification method.

Next, we looked at the average angle of each line between pairs of centroid coordinates, obtained by averaging all slope lengths and taking the arctangent of the mean value. Our results are displayed in Table 2. From these results, it can be seen that using the elimination-by-aspect heuristic results in more vertical eye movements than when using the as-if heuristic. This is as expected, given the functional procedure for each heuristic. Thus, the slopes could give us some insight into making the final classification decision.

<table>
<thead>
<tr>
<th></th>
<th>Elimination</th>
<th>As-if</th>
</tr>
</thead>
<tbody>
<tr>
<td>Will</td>
<td>76.827</td>
<td>17.039</td>
</tr>
<tr>
<td>Remya</td>
<td>72.265</td>
<td>48.374</td>
</tr>
<tr>
<td>Golnar</td>
<td>89.977</td>
<td>65.073</td>
</tr>
</tbody>
</table>

Table 2: Angle of average slope length in degrees for each heuristic on the left eye

7.2 Clustering

As a more technical exercise, we attempted the use of a clustering algorithm as a learning procedure across the data collected from each subject. We produced the plots given in Appendix A. From the results in Appendix A, we can determine that the data with our chosen feature matrix is not easily clustered into two groups using the $k$-means algorithm. Other clustering algorithms exist and should be tested. Collecting more data values to use as potential features would also be useful in determining if clustering is a reasonable approach or not.

The plots of the data show a decision boundary that could be drawn via polynomial regression or $k$ nearest neighbors, based on Cartesian coordinate pairs. However, this decision boundary would be loose, at best.

Based on these results, we were not able to draw any clear conclusions on the data provided from our test subjects. We were, however, able to rule out clustering as a means of heuristic classification across the current feature space. If clustering were to be considered as a potential classification method again, more features would need to be added to the space. We also showed the steepness of the angle of eye movements the elimination-by-aspect heuristic as compared to the as-if heuristic. Finally, we considered the possibility of using logistic/polynomial regression or $k$ nearest neighbors as a classification method,
but dismissed it as being dependent solely on the centroid coordinates and relatively independent of the durations, our other major feature dimension.

8. Conclusion

Analyzing the eye movement patterns for AI and EBA heuristics, we attempted to select the relevant features. Aside from the cell’s internal position in the table studied by each subject, all other inputs are relevant to our target function; however, some inputs are dependent on other values and may be ruled out, depending on the method of analysis. Out of this phase, we found that the duration of fixation and slopes of the eye movements are good sources for determining the heuristic that the subject attempted to use. Although our dataset is too small to draw confident conclusions, the EBA heuristic appears to take more time and exhibit more vertical eye movements, while the AI heuristic movements are shorter and more horizontal.

We also performed a more technical analysis using clustering via the \( k \)-means algorithm. Our results showed that the classification problem was not solvable using clustering, but the Cartesian coordinate pairs do suggest that the problem could be solved by logistic regression or \( k \)-nearest neighbors. However, any calculated decision boundary would be loose, at best, depending only on the values of the coordinate pairs themselves and the duration of fixation. Were any of these methods to be re-considered, more data samples and more feature values would need to be provided.
Appendix A

Plots of clustering results for individual test subjects.
**Group Distribution**

Will: Introduction, Method, Stimulus Generation, General Eye-Tracking Set-Up, Data Collection

Remya and Golnar: Detection and Characterization of Fixations, Participants

Hamid and James: Heuristic Detection through Machine Learning (Theoretical), Participants

**Citations**


