Eurographics Workshop on Visual Computing for Biology and Medicine (2018)
A. Puig Puig, T. Schultz, and A. Vilanova (Editors)

Visual Exploratory Analysis for Multiple T-Maze Studies

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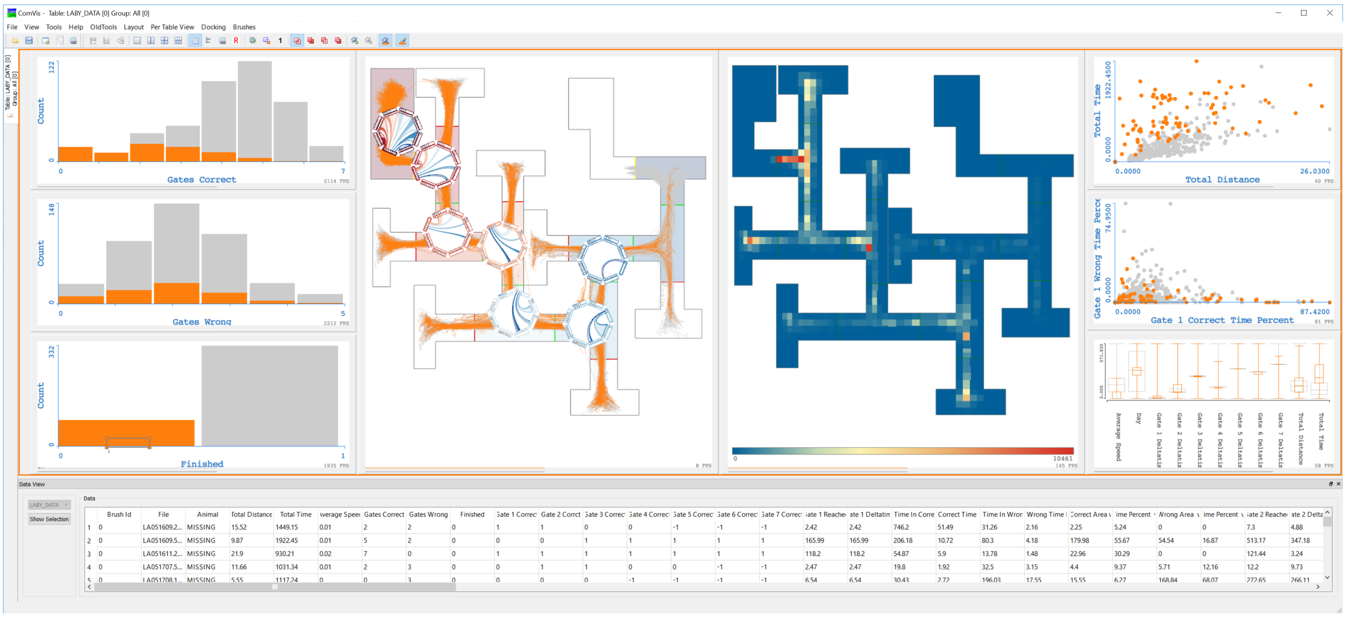

Figure 1: *The T-Maze Explorer – the proposed system for Multiple T-Maze data exploration. The user can combine different interactive views, here t-maze specific views are shown in the middle. In this instance diverse charts – left and right views – give an overview of single or multiple scalar features of animal trajectories as well as detailed descriptive statistics – table in the bottom. All views are linked.*

Abstract

Evaluation of spatial learning and memory in rodents is commonly carried out using different maze settings such as the Multiple T-Maze. State-of-the-art analysis is primarily based on statistics of quantitative measures stemming from animal trajectories in a maze, e.g. path length or correct decisions made. Currently trajectories themselves are analyzed and evaluated one at a time and comparison of multiple trajectories is a tedious task. The resulting findings may not fully answer complex questions that behavioral researchers encounter as well, e.g., why do animals behave in a certain way or can atypical behaviour be detected? This paper describes an innovative approach on how exploratory analysis for Multiple T-Maze studies can be enhanced through interactive visual analysis. We explain our solution for analyzing a whole ensemble of data at once and support the finding of orientational characteristics and migration patterns within the ensemble. We also abstract the analysis tasks for Multiple T-Maze studies and, based on these tasks, we extend a coordinated multiple views system to support the solving of fundamental problems which behavioral researchers face. Besides views of standard charts we deploy a multi-resolution heat map and the Gate-O-Gon, which is a novel visual element. It gives clues on the animals' general movement orientation and distribution of revisited gates, as well as enhances the discovery of patterns in movement and identifying of irregular behavior. Finally we demonstrate the usefulness of the newly proposed approach using a real life data set consisting of 400 Multiple T-Maze runs.

CCS Concepts

• ***Human-centered computing*** → ***Visualization application domains; Visual analytics;***

Keywords: *Interactive Visual Analysis, Animal Trajectory, Movement Data, Spatial Learning, Memory Retention*

DOI: 10.2312/vcbm.20181246

1. Introduction

Scientists studying physiological processes, neural mechanisms, underlying learning process, or aging processes, for example, cannot carry out studies involving humans. Besides obvious ethical issues, conducting such studies with humans would take far too long, and it would be nearly impossible for the study participants to live in a controlled environment, which is essential for such studies. Since a rodent's brain shows significant similarities with the human brain [BN06], rodents represent a premium means for studying such processes. The idea of studying the rodents' behavior and their learning process is not new. Willard S. Small used the behavior of rats in mazes as a measure of learning at the begin of the 20^{th} century [Sma01, SN27].

A better understanding of learning and memory in relation to the aging of rodents leads to a better understanding of similar processes of humans [BLJ94, HES*06, WPF09, LWF11]. Consequently it can lead to efficient measures to cope with the aging society, and moreover to an improved health care. The short life expectancy of rats – the expected lifetime of Sprague-Dawley rats is about 2 years [Bir13] – makes it possible to study aging effects efficiently and in a manageable time interval.

While there are various types of ethological studies, each of them used for different tasks, the Multiple T-Maze is one of the oldest experiments used to study learning processes. Prior to computer age scientists marked rats' paths on a paper using an ordinary pen. Current state of the art methods use computer vision to capture an animals' movement in a maze, making trajectories available digitally. The Multiple T-Maze consists of several T-shaped elements, which are designed to make every T-junction – also called gate – look identical. There are no visual clues which can be memorized. For each T-junction the rats have to memorize if a right or a left turn leads to the successive gate. Interestingly the standard method is to compute various scalar parameters from trajectories, followed by computing descriptive statistics for the extracted parameters. In the case of a Multiple T-Maze the scalar values that are frequently used include: total time needed to reach the end area, total way traveled, total way in correct and wrong direction, number of correct (and incorrect) decisions at the gates. Once all observations are carried out, extracted scalar features are analyzed using standard statistics; the trajectories themselves are seldomly inspected. However, if they are checked, usually it is impossible to evaluate a single trajectory at once.

Motivated by these shortcomings and an approach for interactive visual analysis of open field studies [MWSB12], we introduce a novel approach for the analysis of Multiple T-Maze data. In addition to descriptive statistics, we facilitate the analysis by means of coordinated multiple views and user interaction. In order to do so we carefully studied the typical Multiple T-Maze analysis process together with domain experts and afterwards abstracted all involved analysis steps into clear tasks. Based on these tasks we decided not only to rely on scalars and single trajectories, but to include whole ensembles into the analysis. We chose interactive analysis in combination with conventional statistical analysis as they offer new, diverse possibilities and therefore may lead to novel findings. In addition to standard views, we introduce a Multiple T-Maze view which supports different data abstractions. We also introduce the Gate-O-Gon, a visual element placed at gates which summarizes the most important information to study reverse direction movements. Results appear more traceable for the observer, thereby possible findings of abnormal movement patterns can easily be detected. The main contributions of the paper can be summarized as follows: **(1)** Task abstraction for Multiple T-Maze analysis, **(2)** A novel interactive visual analysis approach using trajectory ensembles and supporting the execution of the identified tasks as well as a t-maze view with different visual abstractions, **(3)** the Gate-O-Gon, a visual element depicting most important characteristics of reverse movements through a Multiple T-Maze.

We summarize related work in the next section and provide a brief domain background in section 3. Section 4 describes the abstraction of analysis tasks and section 5 introduces the new views and our integrated approach based on the identified tasks. Section 6 describes first results from an informal case study where we illustrate the newly proposed approach using a Multiple T-Maze data set consisting of around 400 observations. Finally section 7 concludes the paper and provides insight into possible future work.

2. Related Work

Our work is related to several research directions as our approach involves an interactive visual analysis system which takes advantage of humans in the exploration loop and descriptive statistics evaluations. Such combinations belong to the field of visual analytics [TC05, KKS*11], whose systems have been deployed in numerous domains. In addition we rely on the well known coordinated multiple views paradigm [Rob07]. Apart from that our work is heavily influenced by the research of way-finding and movement data.

Probably the most related paper to ours is our previous work on interactive visual analysis for open field data [MWSB12]. All contributions from our 'open field data' work, such as the cumulative path view, can be applied to the Multiple T-Maze, but due to different tasks they are not in focus for Multiple T-Maze data. In the current paper we deal with the Multiple T-Maze, focus on task abstraction, introduce different abstractions on trajectory visualization in a maze, in addition to the Gate-O-Gon, a novel visual element for visualizing movement between gates. In a previous paper [SBW*14] we described the Multiple T-Maze tasks and introduced an early design for the Gate-O-Gon. In the early stages of the T-Maze Explorer (described in section 5) we closely involved domain experts from the field of behaviorism. These experts provided us with useful insight and feedback, along with the t-maze ensemble data set we used for testing. The tool was extended to accommodate changes in the task abstraction; equipped with additional tools such as the multi-resolution heat map and the single-trajectory explorer. Further we did a first evaluation as described in the informal case study in the last section.

Analysis of various movement data is a well researched topic in Visual analytics. Andrienko et al. [AAB*13] describe visual analysis of movement data, combining interactive visual displays, cognition and reasoning with database operations and computational methods. Many papers deal with more specific movement tasks, for example movement in sports [SJL*18] or movement in air traffic [AAFG18]. Although papers on animal movement exist, they mainly relate to animals moving in the wild. Animal movement ecologists try to distinguish and understand such movement patterns. Slingsby and van Loon [SvL16] describe a visual analytics system for GPS log data of animals. But our underlying movement data is different as the animals are moving in a maze, and the basic task is to study their learning process; how they acquire spatial knowledge or how fast they learn the correct path through the maze.

Another application area for way finding tasks is psychology. Siegel and White [SW75] study the development of spatial representations of large-scale environments for humans. Montelo et al. [MHRW04] review research on how people remember spatial properties (location, direction, distance, etc.) of large-scale environments in which people live. Ji-Sun et al. [KGMQ08] deal with way-finding in a virtual environment. All this research involves humans. It is not easy to create a representative group with standardized environment. In case of research on rodents it is easier to ensure stable conditions and it takes less effort to perform long term studies (relative to the expected life time of the subjects). Rodents in the wild live in a system of tunnels, therefore it is essential for them to acquire good spatial knowledge [BLJ94]. There are numerous studies analyzing rats' behavior in a Multiple T-Maze, a means for testing cognitive stimuli, the learning and memory processes. The Multiple T-Maze is a well defined and described experiment [HEB*00, PJCK03]. Bubna-Littitz et al. [BLHKN81] found out that the t-maze is the best mean for studying the learning process as variations appear much earlier than in other methods.

In the "way-finding" research, authors typically use only simple scalar features, such as total distance traveled or time needed to reach the end. Based on overall statistics of these features conclusions are made. We, in contrast, propose to deepen the analysis and extend the use of descriptive statistics of features by computing these needed statistics for the whole ensemble set or for a distinctly selected subset and furthermore provide ways to show the underlying paths, on demand all at once. By doing so, we offer new analytic possibilities and ease the posing of hypothesis significantly. At the same time, a comparison with standard methods is problematic, as they do not support such advanced analysis.

3. Application Domain Background

This section caters to the specific domain background, which our work is built upon. First we elaborate on the science of ethology and animal behavioral studies. The second part describes the outline and characteristics of the Multiple T-Maze. Lastly we portray the Multiple T-Maze of our specific underlying experiment.

Animal Behavioral Studies

The scientific study of animal behavior has its roots in Charles Darwin's and his predecessors' scientific theory on evolution through natural selection. This natural history approach founded the sciences of animal ecology and ethology. Animal ethology is recognized as an evolutionary, necessary trait with focus on studying behavior under natural conditions, whereas behaviorism studies behavior under laboratory settings with controlled stimuli and conditions. Main aspects of animal behavior studies include communication, learning, emotions, culture, and sexuality. Fields of application range from anthropology, artificial intelligence or neuroscience to linguistics and many more [BRI18]. Scientists are studying animal behavior in hope of getting a better understanding of similar processes in humans, as for example rodents' brains exhibit structures similar to humans' [BLJ94]. One application area of significance is the study of mammals' attentiveness, learning and retentive ability to gain insight on how the mammal's age affects these characteristics. Such research is especially inquisitive as we are faced with an inverted population pyramid, where the part of population in retirement is steadily increasing. By studying the cognitive abilities and processes in animals, especially rodents, scientists hope to find effective means to combat the decline in mental health and memory of our aging population [Bir13]. Experiments based on animal models ensure stable conditions in lab environments while delivering insight into molecular, genetic and cellular mechanisms which explain the impact of cognitive and physical activities on cognitive abilities [Wei08]. Conducting behavioral experiments that directly involve the observation of humans is problematic as massive invasive measures into their life would be necessary to provide a stable and reproducible environment. Also diverse experiences and histories of humans would lead to great variances in the underlying data. This variance would be too broad to offer scientifically profound findings.

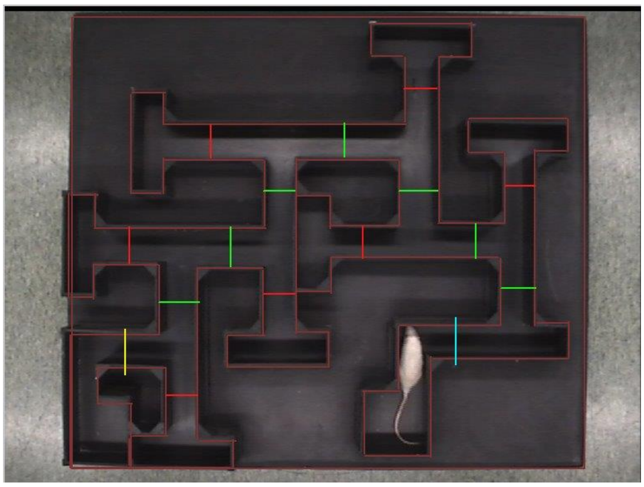

Figure 2: *The Multiple T-Maze used in our experiment with a rat sitting in the goal area. the maze outline as well as gates (green lines for correct corridors and red ones for dead-ends), start (yellow) and goal (blue) area are superimposed on the camera image.*

Multiple T-Maze

The Multiple T-Maze (MTM) is a method for operant conditioning in a setting with controlled conditions, introduced by W. S. Small [Sma01]. It is widely used for cognitive stimulation and as a tool to inspect learning aptitude, retentivity or memory impairment [SN27, PSHL09]. The Multiple T-Maze qualifies for analysis as it clearly shows the differences in learning ability between diverse testing groups. It can be shown that rats are prone for latent learning and use cognitive maps when placed in a Multiple

T-Maze [Wei08]. The t-maze is a simple maze shaped like a symmetrical T element, with a start corridor and a junction leading to a left and a mirrored right arm. At the junction no visual clue as to the correct arm is given. Single t-maze experiments can include a reward in one arm or different rewards in both. It answers questions such as if a rat has a side preference, if they alternate between the left and right arm or if they can be trained to choose a particular arm. In the MTM a given number of such T-segments are fused, with the junction having a correct segment, leading to a successive T-segment and as such nearing the goal, and an incorrect segment, ending in a closed off corridor or dead-end. Consequently this gives the MTM the trait of only having one valid path from start to end. Utilizing innate properties of these paths or trials permits well-founded scientific analysis of their behavior. Multiple trials through the maze are compared to observe memory formation and, given a prolonged break between test trials, makes evaluation of memory retention possible. Trials can be positively influenced by letting rats learn latently, where they free-roam inside the maze before the first rewarded trial. This facilitates the use of a cognitive map rats had generated during their initial exploration. MTM can be divided into different types; place learning or response learning types. In the former, visual cues exist outside a maze, like a window or a spotlight above the reward area. Here rats may include these cues in their cognitive map to memorize the shortest way. Place learning is part of the cognitive map theory. In response learning, belonging to the stimulus-response theory, rats might learn the distinct patterns of a maze, e.g.: 'right, left, left', based on their past trials. Response learning is insusceptible to rotation or repositioning of the maze. The Multiple T-Maze is typically used to evaluate spatial memory by means of path length, successful finish, correct/incorrect choices, time spent on correct/incorrect path, and more.

The Multiple T-Maze used for the underlying experiment of our work consists of 7 attached T-segments, forming 7 decision spots, as well as a designated start and end area. It measures $140cm \times 140cm$ (Figure 2.) The experiment was carried out over the course of 2 weeks. The first week tested the short term memory. Rats were placed into the maze three times a day, from Monday to Friday. In the second week rats were placed into the maze only once on Friday to test their long term memory. To motivate the rats, a reward (food) was placed in the end area. After each run the maze was thoroughly cleaned to remove any lingering scents or other signs from the previous rat to prevent this influencing the following runs. The rats were tracked using a video camera in an infrared lit room. Tracking started once the rat left the start area and ended when it entered the end area or time ran out. This experiment and the resulting 400 digital trajectories are the basis for our visualization approach.

4. Work-flow Demands & Task Breakdown

The state of the art analysis of Multiple T-Maze experiment results consists of computing statistics of scalar descriptors, computed from trajectories for groups of animals. On a very high level, researchers are interested if an animal reached the end area or not. The next level of analysis represents analysis of the time needed to reach the end and the total way traveled. For many experiments

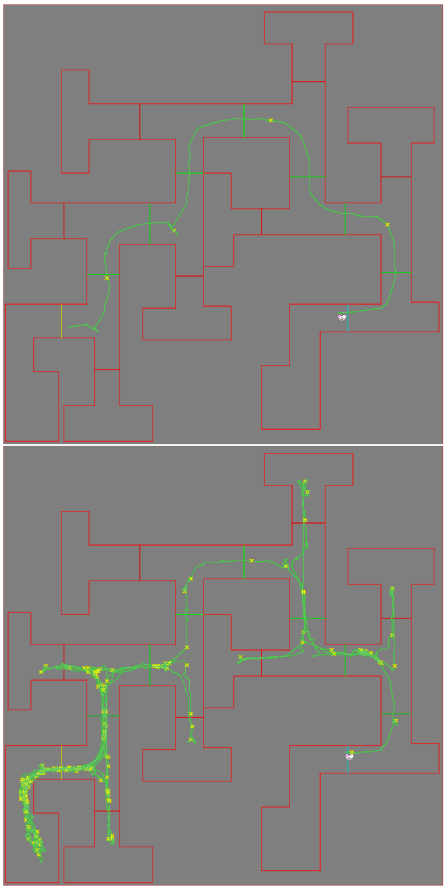

Figure 3: *Two single trajectories from our experiment where the goal was reached, superimposed on the maze.* ***Top:*** *The most efficient animal, ANIMAL 265 – total time: 23 seconds, total way: 2 meters.* ***Bottom:*** *The least efficient animal, ANIMAL 320 – total time: 845 seconds, total way: 22 meters.*

the analysis ends here and researchers conclude if an animal's spatial memory improved with, for instance exercise or certain drugs, based on the gained descriptive statistics.

Such an analysis is certainly valuable and can already reveal insight in overall results. But, is that all? Can we support researchers in a deeper analysis, in more complex analysis tasks? We argue that interactive visual analysis can improve the process and that it can enable much deeper insight in the animals' behavior and learning process. A visual aid enhances the humans ability to efficiently extract and compare information.

Figure 3 shows trajectories of two animals that successfully completed the task — they reached the end area, and both made seven correct decisions (at each junction their first choice was to turn correctly). Nevertheless, one of them (top) needed 23 seconds to accomplish the task and walked 2 meters in total. The other one needed 845 seconds and traveled 22 meters. The quantitative data about time and length clearly indicates a large difference between two paths, but seeing the trajectories themselves in a context with all others, potentially reveals new insight into their behavior and learning processes.

Together with researchers from the field, we investigated the work flow when analyzing trajectories and abstracted diverse tasks to complement their usual work. We believe that these tasks, carried out on different analysis levels, can greatly simplify current work-flow and provide a device for complex analysis and additionally allows the posing of ambiguous questions. We classify analysis tasks depending on the analysis level. On the highest level analysts want to understand basic ensemble characteristics: How many animals reached the end? Does the overall time decrease as the animals learn? Do they remember what they learned in a week? Current state of the art methods can answer these questions.

Once an overall understanding is gained, analysts switch to the next lower level to identify typical movement patterns. Corresponding questions would be: Are there frequently taken paths? Are there places in the maze where animals spend more time for some reason? What is the most frequent sequence of traversed gates for animals that finish or did not finish the test? Many such questions can be posed, and they can be answered with appropriate visualization and interaction. We call such tasks medium level tasks, as they require a certain drill-down into the data, but the analysis still deals with a group of animals.

Finally, following the Shneiderman's visual information-seeking mantra [Shn96], we end with the lowest level — details on demand. An individual animal and its path is in focus here. Besides detailed quantitative evaluation of the path — time and way broken down to segments — analysts can also see the path with superimposed additional information in order to inspect the animals speed and orientation. An animation of the path with time-dependent information can help to better perceive its movement.

The analysis tasks can be abstracted as follows:

(i) **High Level Tasks**

H1 Characterize the whole ensemble by means of descriptive statistics.
H2 Identify possible outliers in the ensemble, not only in quantitative measures, but also at the paths level.
H3 Identify typical paths, especially the paths in wrong direction.
H4 Classify maze parts depending on popularity.

(ii) **Medium Level Tasks**

M1 Analyze subgroups of the ensembles by applying high level tasks to reasonable subgroups.
M2 Analyze maze parts at different granularities (segmentation finer than gates).

(iii) **Low Level Tasks**

L1 Provide detailed statistics for an individual animal.
L2 Enhance trajectory with notion of speed.

5. Integrated t-maze Data Analysis and Gate-O-Gon

Data Analysis

Analysts are used to gaining first impressions of the data set by means of descriptive statistics. Though there is no need to redevelop this well-established method, we believe it is possible to improve it to lighten analysis of the whole ensemble **H1**. For this, we developed a tool for exploratory analysis of MTM data, the *T-Maze Explorer*. This explorer is based on the Coordinated Multiple View (CMV) system ComVis [MFGH08], developed at the VRVis Research Center to assist a rich diversity of analysis tasks, from a variety of research fields, with interactive visual tools. The T-Maze Explorer was designed to support all identified analysis tasks and provides diverse linked views, depicting single scalar attributes (e.g. histogram), multiple scalar attributes (e.g. box plot, scatter plot) or complex data such as trajectories themselves or cumulative distance traveled (curve view, e.g.). Likewise we compute all common statistics used in MTM studies, and provide a table view that show all values on demand. In addition, some views are enhanced with descriptive statistics, such as parallel coordinates, in order to support quantification of the analysis results. Figure 1 shows a screenshot from an analysis session of Multiple T-Maze data, using the T-Maze Explorer. On the left side we used histograms to show the distribution of correct and wrong gates as well as if an animal finished the maze or not. On the top right side scatter plots are utilized to illustrate the correlation between total distance and total time. Box plots give an impression of the speed of the animals, broken down into average speed, speed per each gate and total speed. The middle views depict the t-maze view, showing the outline of the used Multiple T-Maze, with each correct gate segment softly emphasized and various options. These include the Gate-O-Gons, the multi-resolution heat map, and the single trajectory mode, which will be explained in the following paragraphs. In the middle left view the Gate-O-Gon overview was selected, in the middle right the heat map. The use of a CMV system allows us to display this variety of scalar statistics on a single screen. It sets all views in relation and facilitates gaining insight on a high level. As all views are linked, brushing one view and hence selecting a subset of the whole ensemble as required for **M1**, highlights the selected subset and has direct effect on all other views. To keep the context the whole dataset is still visible but grayed out whereas the selected subset is dyed orange. In the T-Maze Explorer we can also easily identify statistical outliers and explore these via brushing (**H2**). But standard statistics do not tell us about atypical movement patterns as desired. In addition to identifying animals with peculiar movement in the maze it is significant to pinpoint typical paths and the overall orientation of their movement.

The gates are numbered in an ascending order, beginning with the start area as gate 0, incrementing with each successive gate. Forward movement happens while traversing the gates in an ascending manner, reverse movement vice-versa in a decrementing manner. After consulting our domain experts it suggested itself to focus on reverse movement, as it may be more insightful to determine the reasons behind why animals turn back. Due to the complexity of the reverse movement analysis it is often omitted, although it is considered very important. Though with time, it might become definite that exploring the forward movement might be eligible as well. We are interested in from which higher gate to which lower gate animals went into the wrong direction. Subsequently it might be possible to derive a theory on general movement patterns. With our new approach on visualizing Multiple T-Maze data we believe that we meet the demands of high level task **H2** and **H3** and enable manipulation of subgroups as required for task **M1**.

To make identifying movement patterns possible we first classified the trajectory set on the basis of position and orientation inside the Multiple T-Maze. After loading the trajectory ensemble the first step is to analyze each trajectory separately. As a trajectory consists of coordinate positions, among other parameters, we can split it into forward movement and reverse movement. In the second step we identify the highest gate where reverse movement started and the lowest gate where it ended or where forward movement started again respectively. These start- and end-gates can be grouped into a pair, called gate-pairs. The T-Maze's singularity of having only one correct path from start to end, allows us to identify all gate-pairs for each trajectory in the ensemble. This means that to get to the goal an animal inside the maze, starting in the start area, has to pass gates along the path in an ordered manner, i.e. passing the first, then the second, third gate and so on. If the animal achieved this without making any wrong choice a gate-pair consisting of the start and goal can be formed. This can be done for any gate combination. Focusing only on the reverse movement, we refer to this backtracking from one gate to another as returns of a gate-pair.

Design of the Gate-O-Gon

The underlying data structure for the gate-pairs is an adjacency matrix. The matrix A is of size $n \times n$ where n is the number of gates. Each entry A_{ij} is equivalent to returns from gate j to gate i, where the value corresponds to the total occurrences of gate-pair ij. Figure 4 top shows such a matrix. The data stems from the same trajectory ensemble we used for the case study. This gives us a precise statistic of all rats' returns and permits easy access to the distribution of returns for each gate. When inspecting a particular gate G_i we can further split the returns into incoming and outgoing. *Incoming Returns* are returns from any gate G_j to the inspected gate G_i, with $j > i$. Incoming returns correspond to the entries of row i in A. *Outgoing Returns* are returns starting at gate G_i and ending at any lower gate G_j, $j > i$. Outgoing returns correspond to column i in A.

Visually enhancing the matrix itself does not greatly simplify the analysis task as it does not exploit the innate humans' capability to quickly process information depicted in graphics and symbols. Therefore we tried to find a suitable visual representation of this matrix. An obvious solution would be an adjacency graph showing the whole data, with vertices representing the gates and an edge between two vertices when a return between the corresponding gates exists. In figure 4 we tried visualizing an adjacency graph, using the data of the above adjacency matrix. Clearly this can be analyzed and some insight can be found when addressing the graph in depth. But it is not easy to quickly interpret as one has to look at and compare each number separately, which evidently would not ease the researchers' analysis task. Also this poses a challenge to finding movement patterns in the maze as it only gives insight into whether movement happened between two gates. In Figure 4 we see that no returns between gate 7 and gate 2 appeared. Alternatively we could only show the edges where no movement occurred. But this would leave us blind to the total quantity of movement happening, which is essential to pattern finding as there is a difference if just 2 returns occurred or 100. Based on these limitations we decided

$$A = \begin{bmatrix} 0 & 282 & 111 & 166 & 43 & 76 & 22 & 27 \\ 0 & 0 & 34 & 26 & 6 & 10 & 4 & 4 \\ 0 & 0 & 0 & 49 & 5 & 5 & 2 & 0 \\ 0 & 0 & 0 & 0 & 9 & 5 & 3 & 4 \\ 0 & 0 & 0 & 0 & 0 & 37 & 5 & 7 \\ 0 & 0 & 0 & 0 & 0 & 0 & 25 & 7 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 2 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

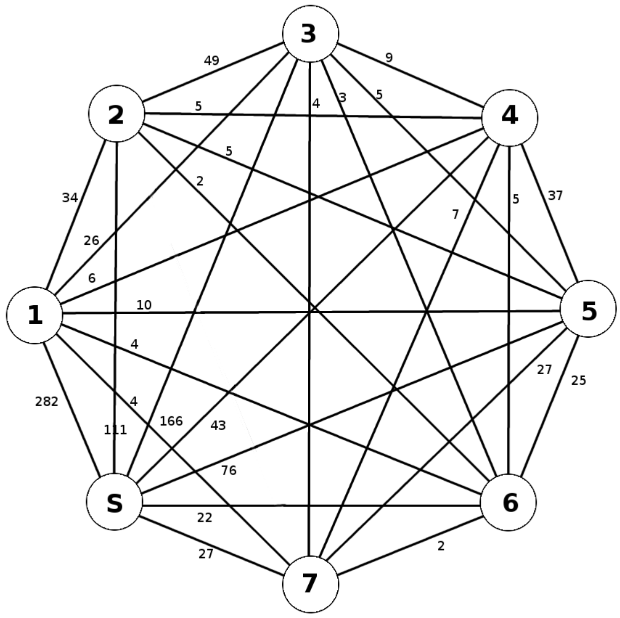

Figure 4: ***Top:*** *Adjacency matrix as underlying data structure for trajectory return movements. Here we can see the adjacency matrix of the case study dataset with 400 trajectories.* ***Bottom:*** *Adjacency graph as first possible visual representation of the adjacency matrix.*

on a gate-based approach, where each gate is symbolized through a decisive graphic. Such symbols should be placed on top of a gate in the t-maze view and depict a summary of the most important information concerning the related gate.

Before deciding on the Gate-O-Gon, we considered diverse solutions for this graphic symbol. One idea was to place a histogram of the incoming returns distribution in the t-maze view, but concluded that this would not greatly facilitate the analysis process. Another approach was to abstract the Multiple T-Maze into a mini version of itself and superimpose it onto each gate inside the t-maze view. visualizing a gate-pair's connection would have been realized by drawing a path between the gates inside the mini t-maze. Downsides of this idea are amongst others that it would be too small and overloaded to inspect. Depicting the quantity of a gate-pair's occurrence would be impossible. Similar problems occur when directly drawing all existing connections inside the Multiple T-Maze corridors. Given the extend of possible returns, it is futile to discernibly draw all inside the narrow corridors of the t-maze.

Ultimately we chose a tree-like visualization, where the root cor-

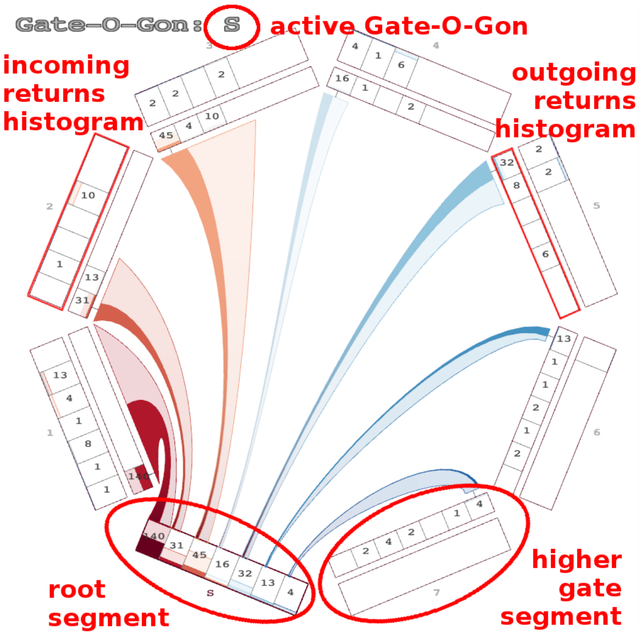

Figure 5: *The brushed Gate-O-Gon associated with the start area. At the bottom left the histogram shows the distribution of incoming returns to the Start area. The other gate sections depict the incoming and outgoing returns distributions. A strap links a bin of the start area histogram to the corresponding gate section. The thickness is related to the incoming and outgoing return. Brushed data is highlighted in full color.*

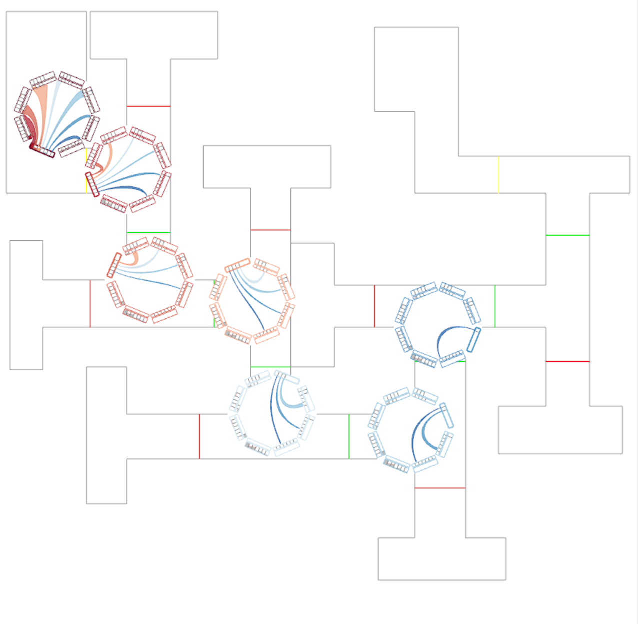

Figure 6: ***Top*** *High level view of the Gate-O-Gon. Summarized information concerning a gate is visualized through a small Gate-O-Gon on top of the T-Section to gain a first impression of the whole data set. From the strap thickness we can see that most movement occured between the start area and other gates, especially gate 1.*

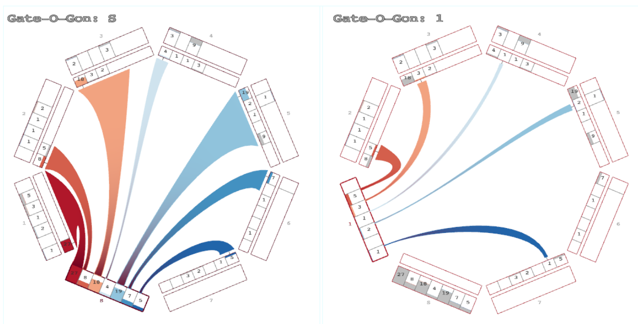

Figure 7: *Two Gate-O-Gons of the same analysis session, illustrating how movements between gates can differ.* ***Left:*** *Gate-O-Gon of the start area, a lot of animals returnt from most higher gates, visible from the thick straps.****Right:*** *Gate-O-Gon of gate 1, where only a few animals returned to in relation to the start gate.*

responds to the inspected gate G_i and the leafs represent all higher gates G_j. Here we can accommodate all desired information, such as all distributions of returns per gate or the quantity of a return. Based on the decision to give each gate a singular visual representation, which should be easy to compare, we arranged the tree into a circular outline and abstracted it to an octagonal shape, as Multiple T-Maze used for our data set consisted of 8 gate segments. Now every gate segment is represented by an edge of the octagon. Associating an edge with a fixed gate makes the visual elements self-similar. For each gate representation the root changes in a clockwise manner, starting at the bottom left edge for the start area, as seen in figure 5. The last gate has its root on the bottom right edge, next to the start edge, completing the circle. We call this diagram the *Gate-O-Gon*, figure 5 shows the final version of the Gate-O-Gon in a brushed state. Domain experts, which were also involved in the initial design, well received this visualization. Tracking of an animal in the maze stops after it crossed the correct arm of the last T-Segment. Even if the animal turns around after, it is counted as successful finish. Therefore no Gate-O-Gon is necessary for the goal area.

Each gate has its own unique color, echoed in the Gate-O-Gon to emphasize the relation between a segment in the Gate-O-Gon (an edge of the octagon) and its associated gate. Researchers can choose between different color schemes in the tool but as standard we chose a red-blue color scheme where each color is easily distinguishable. The first gates are colored red, changing to blue the nearer they are to the goal area. This is an analogy to the distance traveled; Animals returning to the lower gates are far away from the goal and therefor have not learned the maze structure yet, hinted at by the negatively insinuated red color. Blue indicates a short distance to the goal; a desired outcome.

After having settled on the basic design of the Gate-O-Gon we added additional information relevant to a gate. We could have displayed the distribution of returns for each gate in a conventional histogram though navigation could prove difficult. Loosing the context of the distribution of other gates is likely, especially when viewing all distributions in the overview, making it challenging to draw conclusions, whereas our goal is to simplify this process. As each edge corresponds to a specific gate G_i, we can enhance this edge to show the distribution of the returns related to G_i, depicted as histograms. Since our first design, we extended this histogram area in the Gate-O-Gon to show the outgoing in addition to the incoming returns. This gives us additional insight into where else animals returned to from a specific gate, besides the currently inspected one, as well as the relative quantity. The histogram bins related to the inspected Gate-O-Gon are displayed in the respective gate color, whereas the histograms of the other gate segments are grayed to give context but leave focus on the current gate information. This summarized view of all desired information helps in tackling the high level tasks.

A gate-pair is depicted through a strap between the root – the currently inspected gate – and a higher gate. This allows us to easily perceive the return movement related to a gate. As each gate in the t-maze view is topped with a Gate-O-Gon, we get an overview of all reverse movement inside the maze (**H3**). From the visible strips we can easily spot all existing incoming returns. The thickness of this strap stems from the total appearances of a gate-pair. At the root Segment, the strap thickness is relative to the total incoming returns, at the higher gate segment it is relative to the outgoing returns. Scaling of the histogram bins and strap thickness is influenced by a set of scaling parameters. These scaling parameters can be the total counts of returns in each gate segment or maximum return count of all gate-pairs. This allows for exploration of the same data set or subset in different contexts.

Now we are able to identify outliers in the movements as requested of task **H2**. A thick strap depicts that a lot of animals chose to walk this way, which can indicate typical movement. A thin strap can hint to irregular movement. How singular Gate-O-Gons from the same analysis session can look like is evident when comparing the Gate-O-Gons of the start area (left) and gate 1 (right) in figure 7. The striking difference is the thickness of the straps. In the left Gate-O-Gon most straps are very thick, making it apparent that most animals returning from a higher gate traveled to the start area and only a few to other gates (evident in the outgoing returns histogram). The same does not apply to the Gate-O-Gon on the right . Here the straps are thin. Also the root histograms differ greatly. Compared to the start area, gate 1's incoming returns are almost nondescript.

Following Shneiderman's visual information-seeking mantra [Shn96] again, selecting a single Gate-O-Gon moves from an overview of the whole maze to detailed information of a single gate. Here we show the absolute quantity of the distribution. Additional information on a gate-pair and its proportion in the selected context is available via 'mouse-over' effect. On this level we can also apply brushes based on the movement orientation (**M1**, **M2**). For example, we can select the subset of animals which had reached the last gate but then decided to turn back to the start area. For this we can pick the Gate-O-Gon corresponding to the start area and here select the last bin in the incoming returns histogram of the current gate, which is equivalent to the gate-pair of start and 7^{th} gate, or $A_{0,7}$ in the adjacency matrix.

Design of the Multi-Resolution Heat map

A multi-resolution heat map gives additional understanding of where animals spent most of their time, respectively which parts of the maze are avoided. We analyze the trajectories' coordinates on their positions in the t-maze. By accumulating the occurrences, we can show exactly how much time was spent in each gate segment. Figure 9 Top shows the gate-based heat map, indicating that animals take their time in the first parts of the maze and move faster the further they get. With this heat map it is easy to spot popular gates but it gives no clue to where animals linger inside a gate segment. Therefore we extended the heat map to a flexible area size, or granularity. Granularity of 0 shows the accumulated time on a gate level. Increasing the granularity is splitting the heat map area from the whole gate segment into smaller regions. The regions size changes depending on the granularity level, similar to a divide-and-conquer principle. The analysts can freely adjust the heat map granularity, depending on their needs; from a general outline of which gates are frequently accessed (**H4**) to identifying hot-spots in a particular part of the maze (**M2**). This allows hypothesizing on the behavior. In figure 9 a granularity level of 0 and 4 was used. Here the hot-spots are the start area, right where animals enter the maze, and at the T-junctions, indicating that they pause and try to orient themselves in the maze, before resuming movement.

For questions related to a single animal or for a more detailed inspection of an outlier trajectory we provide a view where analysis of a specific trajectory is possible, based on our previous work [MWSB12]. Detailed scalar statistics of an individual animal (**L1**) is available. Selecting a single path allows the examination of the trajectory with a notion of speed (**L2**). The path of the animal can be viewed as an animation, showing the position of the mouse depending on the time. The path can also be depicted as a static, with just the last n positions, like a fading tail. Another option is to display the trajectory with small x-markers, indicating the position every 5^{th} second. In figure 8 the marker-based option was selected.

6. Informal Case Study - Multiple T-Maze

In order to evaluate our newly proposed approach, we briefly describe the first evaluation of the system, based on our 400 trajectory data set. We start with a setup as shown in Figure 1. We brush the paths in the wrong part of the gate 7. A simple line brush is used (Figure 8a.). The correct gates count histogram shows that there are some animals with 7 correct gate decisions who visited the wrong part of the gate 7 (Figure 8b.). The correct or wrong gate attribute indicates the first decision made at a T-junction. The animal can turn around then, go to the previous gate or go to the dead end part of the gate, the first decision remains correct. So, seven correct decisions means that the animal made the correct decision first at all gates. We drill down and select all trails with seven correct decisions in the histogram (Figure 8c.). Two trajectories remain. One of them finished the experiment successfully while the other did not. The total way and total time for the two animals differ significantly (Figure 8d.). Selecting the trajectory from the animal that did

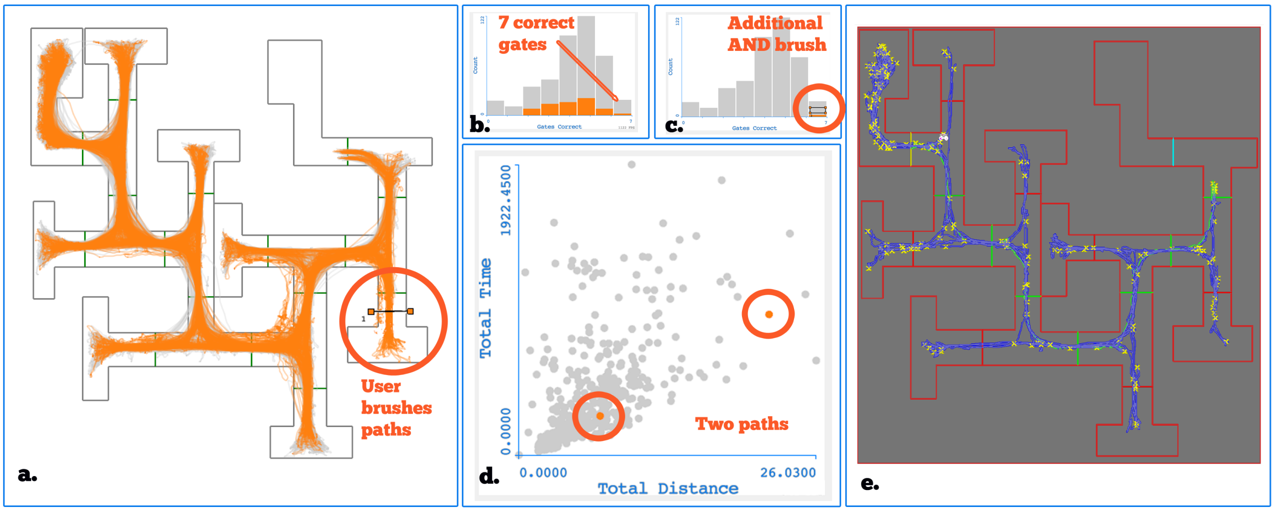

Figure 8: *A possible analysis session for the ≈ 400 trajectory ensemble data, using the T-Maze Explorer.* ***a)*** *shows all the trajectories of the dataset superimposed on the Multiple T-Maze. A brush was used to select all trajectories where animals went into the dead end corridor of gate 7.* ***b)*** *A histogram showing the distribution of correct decisions, before brushing.* ***c)*** *The histogram from b) after a brush to 7 correct gates was applied. It now highlights the remaining trajectory data.* ***d)*** *A scatter plot showing the correlation between Total Time and Total Distance. Only two data points meeting the brushed criteria are highlighted.* ***e)*** *Single Trajectory View static depiction of speed. Yellow markers indicate the animals position every 5 seconds. Here the trajectory with higher total time and distance from the two brushed trajectories was selected. The animal made the correct first choice for each gate but ventured back to previous gate segments quite often.*

not finish the experiment, we can examin it in detail in the single-trajectory explorer. We see that the animal visited all segments, the right and the wrong ones, of all gates (Figure 8d). It goes forth and back, and the time expires before it manages to find the end area, although it was so close. Interpreting this behavior is not easy, as it is a clear exception. Finding such interesting cases is much easier with explorative visual analysis than by means of descriptive statistics. Is our experiment valid with such outliers? Why did the animal behave in this way? There are many questions which can be posed, and domain experts have to answer them.

A rich set of scalar features, usually computed, can be partially used to detect such changes. Still, seeing all runs and interactively selecting interesting patterns is much more efficient. An interesting, important feature is the decision for traveling in the wrong direction. If an animal enters a gate where it has already been it is considered a wrong direction. The wrong way can be explicitly highlighted in the T-Maze Explorer, and the Gate-O-Gon depicts a summary of start and end gates of the wrong direction sections. Figure 10 shows the Gate-O-Gon for gate 1 of this analysis session.

Examining the overview of the Gate-O-Gon view we can see that most animals go back all the way to the start area. This is an interesting finding, which needs further examination. The gate 1 is the second most often visited gate. Most animals coming back to gate 1 (and do not proceed further back to the start area) are coming from gates 2 and 3 (10). When we look at the outgoing returns of gate 2 and 3 we see that only a small part of animals, which turned back in these gates, stopped in gate 1. Most went back to the start area. We also see an anomaly for gates 5 and 6. For all other gates, the outgoing returns to other gates is low, but for the gates 5 and 6 the last bins are large. This means that many animals from gate 6 go back to gate 5 and then go forward again, and that many animals, once they reach gate 5 go back to gate 4 only, and go forward then. This is another unusual finding which definitely requires further investigation.

The heat map shows how much time the animals spent in individual T-segments (figure 9top). The tracking begins as soon as the animal leaves the start area. A red start area in the heat map shows that there are many animals that dwell here or go back to the start area. In an ideal case the animal never goes back (see Figure 3 Top). The heat map also shows that, as we approach the end, animals spend less and less time in the gates' areas. Except for gate 1 and 2, the dead end sections are quickly vacated. Basically, once the animals reach gate 6, they are quite fast. We want to know in which specific parts of the gates the animals stay. Therefore we increase the granularity to 4. Figure 9 Bottom shows such a case. Two especially popular areas in the start area are highlighted. Many animals went back to the very beginning of the start area, and even more lingered in the first corner. Other bright areas occur in the T-junctions, especially of the first gates. This can indicate that animals come to a stop at the junction and think about the best way to take next. Other bright spots in the heat map may indicate that the maze is not properly cleaned between runs and that some smell remained. If this is the case, the data of the experiment has to be carefully checked.

7. Conclusions

The T-Maze Explorer is our first approach to facilitating the analysis process of Multiple T-Maze data. We can show that our views

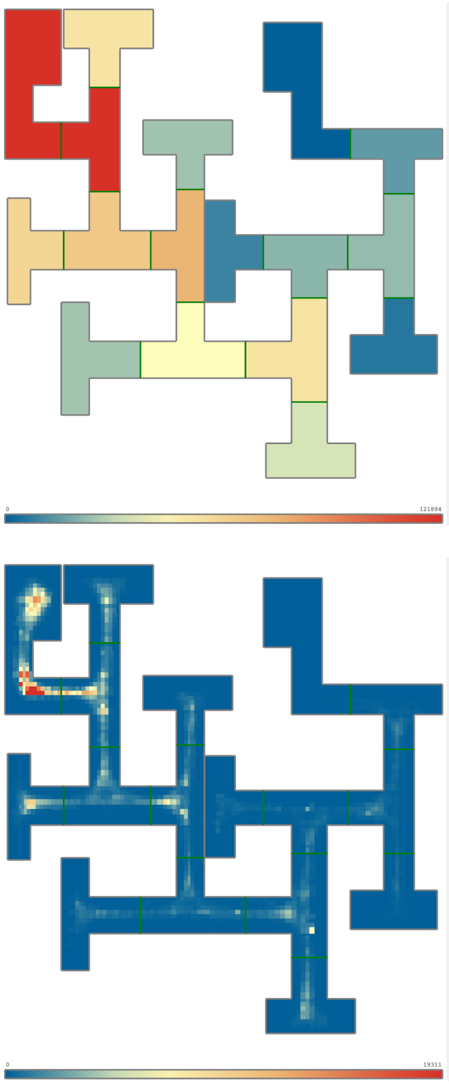

Figure 9: *Multi-resolution heat map superimposed on the Multiple T-Maze: **Top:** Granularity = 0; The values are calculated for each T-Segment, giving an overview of the gate's popularity. Animals spent most of their time in the start area and gate 1 (segments colored in red), on average they stayed in the correct gate segments (light orange) and spent only little time in wrong gate segments (light blue and blue), except for wrong gate 1 and 2. **Bottom:** Granularity = 4; Each gate is subdivided into smaller regions, highlighting hot-spots in the maze. Light areas can be made out in the middle of a T-juncture, indicating that animals paused in the juncture before venturing on.*

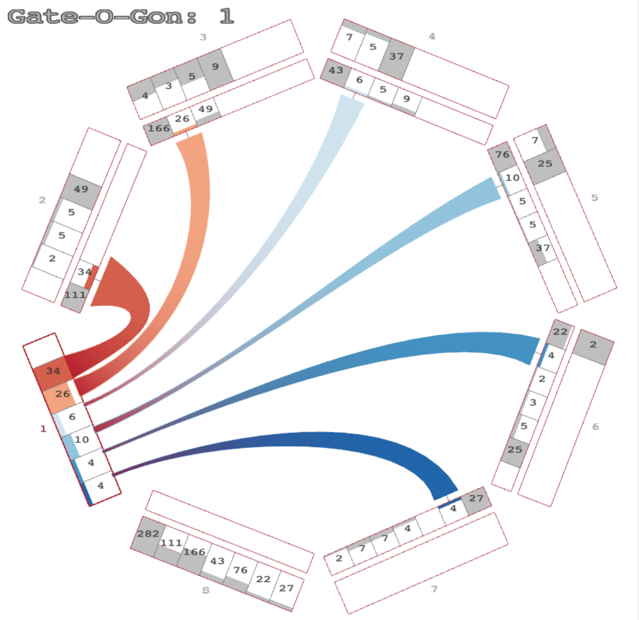

Figure 10: *The Gate-O-Gon for the first gate area. Animals returning until gate 1 (and not further back) came from all higher gates. The root histogram depicts the distribution of incoming returns to gate 1. Each histogram bin is connected to a corresponding gate: the first bin, colored in a lighter red, implies that 34 animals traveled from gate 2 to gate 1, mirrored in the strap between the orange bin and histogram 2. Histogram 2 and higher are divided into two histograms, the outer histogram portraying incoming returns to this gate and the inner one outgoing returns from this gate.*

will increase efficiency and enhance the current work-flow of domain experts. The application is easy to learn and, according to the first informal feedback we gained, it offers completely new possibilities for the data analysis, which is confirmed by our informal case study, where a lot of interesting findings were revealed. Nonetheless an extensive evaluation of our system is needed. For this reason we plan a substantial case study conducted by domain experts. Moreover we are aware that different approaches to solving the tasks exist. The experts' evaluation will show if our tools need further adaptations or extensions. Such future work could include a sequence graph, where we do not only analyze the distribution of revisited gates but record the sequence of visits and find all traversed gate patterns and their frequency. A different approach could be an event graph showing fluctuation of all movement simultaneously. We also plan to exploit computational methods applied to the general trajectory analysis to the Multiple T-Maze data.

8. Acknowledgments

We thank our colleagues from University of Veterinary Medicine in Vienna, Christiana Winding-Zavadil and Michael Balka, for many fruitful discussions and data provided. VRVis is funded by BMVIT, BMDW, Styria, SFG and Vienna Business Agency in the scope of COMET - Competence Centers for Excellent Technologies (854174) which is managed by FFG.

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