Optimality and Space in Weakly Constrained Everyday Activities

Petra Wenzl (pwenzl@uni-bremen.de) ✉
Institute for Artificial Intelligence, University of Bremen, Bremen, Germany

Holger Schultheis (schulth@uni-bremen.de)
Institute for Artificial Intelligence, Bremen Spatial Cognition Center, University of Bremen, Bremen, Germany

Abstract

The action order of most everyday activities is only weakly constrained: When setting the table, for example, the order in which the items are placed on the table does not matter if all required items are on the table eventually. Little is known about how humans deal with weakly constrained sequences. Consistent with research on local optimality of human behavior and the "law of less work", we propose that the order of weakly constrained sequences is not chosen arbitrarily but due to preferences, with the overall goal to minimize cognitive and physical effort. We implement and validate a stepwise-optimal model for table setting, revealing ordering preferences based on distance, functional relations between items, and reachability. The model's success has implications concerning action organization in weakly constrained sequences as well as control of action sequences and provides further evidence on the question of global vs. local optimality of human cognition.

Keywords: everyday activity; spatial cognition; preferences; optimality; action sequences

Introduction

Everyday activities such as cooking, cleaning up, and setting the table, require a complex set of cognitive skills. The complexity of seemingly simple everyday activities is evidenced by the fact that (a) already mild cognitive impairment may interfere with successful performance of highly familiar everyday activities (Gold, Park, Troyer, & Murphy, 2015), (b) healthy adults also exhibit occasional errors such as the unintended omission of subtasks (Cooper & Shallice, 2000), and (c) artificial systems exhibiting mastery of everyday activities remain to be achieved (Ersen, Oztop, & Sariel, 2017).

Given their complexity, the study of everyday activities promises a deeper understanding not only of the involved skills, but also of how these skills interact and are combined in the human mind. Furthermore, a deeper understanding of everyday activities potentially has great applied merit by allowing to better support people to live independently, who otherwise would require professional care to master their everyday life.

In this contribution we consider an important aspect of successful everyday activities, which has not received sufficient attention by previous research: Action sequence organization under weak constraints. While certain actions are crucial for the successful performance of everyday activities, the action order is usually only partially (if at all) determined: If one wants to set the table, the sequence in which the required items are picked up and brought to the table is irrelevant, as long as all items end up on the table eventually. We refer to such action sequences with few or no constraints as *weakly constrained sequences*. Existing research either treats each possible sequence as equally likely (Botvinick & Plaut, 2004) or as idiosyncrasies of the person or situation (Cooper & Shallice, 2000).

We propose that humans neither consider all possible sequences nor randomly instantiate a possible sequence under weak constraints. Rather, we argue that people exhibit *preferences* for certain action sequences. Specifically, based on previous research, we assume that these preferences arise from stepwise optimization of the movement distance subject to functional relations between objects and their reachability. We developed a computational model that implements these assumptions and evaluated it on three datasets comprising human activities during table setting. The model fits and generalizes well across the three datasets lending support to our assumptions. Besides shedding light on the nature of human action organization in weakly constrained sequences, our model's success also speaks to the debate on global vs. stepwise optimality and raises questions concerning the control of action sequences.

The remainder of this paper is structured as follows: First, we give an overview of the role of local optimality, minimization of cognitive and physical effort, and space in the context of everyday activities. Subsequently, we present and validate our stepwise-optimal model for action ordering in weakly constrained sequences. We conclude with a discussion of our results and issues for future research.

Optimality, Minimization of Effort, and Space

Optimality

According to optimality theory, human behavior can be assumed to approximate an optimal function when compared to a mathematically determined ideal behavior (Chater, Tenenbaum, & Yuille, 2006). While the paradigm of universal rationality postulates that prediction strategies for human behavior should be as general as possible, adaptive rationality states that good prediction methods are adapted to the structure of a given *local* environment, providing highly efficient solutions for a specific task (Schurz & Thorn, 2016). Adaptive rationality assumes that all successful cognitive methods used by humans are locally optimal.

Jones and Love (2011) propose that when trying to explain human behavior through rational analysis, mechanisms such as knowledge representation and cognitive processes have to be taken into account. This is consistent with the concepts of *bounded rationality* (Simon, 1955) and *optimization under constraints* (Sargent, 1993), which both take limitations in knowledge and processing capacity into account and have been substantiated by other research, (see e.g. Icard, 2018). To identify effective mechanisms that can plausibly be implemented by a resource-bounded human brain, Bayesianism is assumed to offer a useful analysis tool for specific cognitive functions.

Research on sequential information search and planning indicates that humans tend to use heuristic stepwise-optimal strategies rather than planning ahead (Meder, Nelson, Jones, & Ruggeri, 2019). Stepwise-optimal strategies can be considered as locally optimal, since they only try to optimize for each action step rather than for the whole action sequence.

As everyday activities are complex tasks, we consider strategies aiming to find the globally best task solution to be computationally expensive and therefore unfeasible. Taking limitations in processing capacity and knowledge into account, we propose that humans deal with such activities by using a locally optimal model (heuristic) to choose their next action.

Minimization of Effort

According to Hull's "*law of less work*" (Hull, 1943), physical effort tends to be avoided, if possible. The concept has since been expanded to include cognitive effort, arguing that physical and mental effort are equally aversive (Kool, McGuire, Rosen, & Botvinick, 2010). This avoidance of effort is evident in people organizing their task environment by clustering task-relevant items and centralising frequently used items (Solman & Kingstone, 2017). When organizing objects to reduce physical effort, spatial habit competes with the goal to minimize effort, resulting in a reorganization of items only if the costs for maintaining spatial habits become more noticeable (Zhu & Risko, 2016).

The concept of an internal cost of cognitive effort has been particularly influential as it explains the (globally) suboptimal strategies frequently observed in humans – favoring simplifying strategies (e.g., heuristics) can be subjectively optimal when reducing the internal cost of mental effort outweighs the benefit of a more accurate strategy.

In order to explain how cognitive effort can be reduced, Clark (1996) proposed the concept of *external scaffolding*. Accordingly, exploiting external structures facilitates human problem-solving and allows for reducing the cognitive effort of a specific task by offloading (part of) the problem solution to external scaffolds such as tools or memory aids. According to Wilson (2002), strategies to offload cognition are used particularly often in the context of spatial tasks. The environment can be used to avoid having to encode or actively represent stimuli or tasks, e.g., by laying out the pieces of an object to be assembled in roughly the order and spatial relationship they will have in the finished state.

Against this background, we assume that humans exhibit preferences for action sequences that minimize the effort required for task success. We use the term *preferences* to refer to a concept with the following characteristics: 1) They determine a (partial) order on a set of options, 2) individuals may not be aware of alternative options that have been neglected in favor of the preferred option and 3), they do not emerge from a mechanism specifically designed to generate preferences but are the result of more general processing principles in human cognition.

Space

All human (everyday) activity takes place in space – required objects for a given activity are located in the physical environment, and movement within this environment is necessary for performing the activity. Spatial properties, e.g., distance, are also directly related to the required physical effort. While determining the action sequence for performing a specific activity, the spatial setup of the environment may impose constraints, such as having to move one object first before the object located behind it can be reached. Even if there are no hard constraints, there are a number of reasons to believe that the order of actions in weakly constrained sequences is determined by the spatial environment and its mental representation.

According to Kirsh (1995), the organization of objects in physical space aims to minimize cognitive effort and to facilitate the performance of everyday activities. People use spatial arrangements to serve as cues what to do next by simplifying internal computation (e.g. by arranging objects in the kitchen in a way that it is obvious which vegetables need to be cut, washed, etc. in the next step). Minimizing (computational) effort by using the properties of the spatial environment to facilitate one's actions is also consistent with the theory of strong spatial cognition (van de Ven, Fukuda, Schultheis, Freksa, & Barkowsky, 2018).

Another crucial characteristic of mental spatial representation is their organization by region (McNamara, 1986). When planning a route in a regionalized environment, humans prefer routes that cross fewer region boundaries (Wiener & Mallot, 2003) or allow entering the target region more quickly, even if shorter routes exist (Hochmair, Büchner, & Hölscher, 2008). While the cited studies apply to environmental spaces, it seems reasonable to suppose that regionalization may also be of importance in small-scale vista spaces, because traversing space according to regions reduces the overall distance and therefore the necessary effort.

Taking the above considerations into account, we assume spatial properties of the task environment, i.e. distance and physical constraints, to be an important factor when deciding for the next action in everyday activities.

Stepwise-Optimal Model for Table Setting

Consistent with humans favoring stepwise-optimal strategies over planning ahead (Meder et al., 2019) and the "law of less work" (Hull, 1943; Kool et al., 2010), we assume that table setting follows a stepwise-optimal strategy. Taking the role of preferences and space in everyday activities into account, we propose that humans exhibit specific preferences for action orderings: The next item to be picked up and taken to the table is assumed to be chosen based on the current location as well as the perceived cost of each possible action, with the lowest-cost action being chosen.

Based on research on how the spatial environment is used to facilitate task performance, i.e. intelligent use of space (Kirsh, 1995), external scaffolding (Clark, 1996; Wilson, 2002) and strong spatial cognition (van de Ven et al., 2018), as well as preferences regarding route planning (Wiener & Mallot, 2003), we expect preferences to take specific constraints into account:

- *Distance* (minimizing traversed distance by collectively picking up items that are stored in the same location),
- *functional relations between items* (saucer goes below cup and should therefore be taken first, so both items have to be moved to and placed on the table only once), and
- *reachability* (picking up items from, e.g., a counter top, is considered less effortful than picking up items stored in a closed cupboard).

We propose these constraints as likely factors driving possible preferences. We do not claim that these are the only factors giving rise to possible preferences. However, based on the existing research reviewed above, we assume that these constraints have a strong influence on human behavior in everyday activities.

We implemented our three core assumptions in a computational model. The model approximates stepwise-optimal behavior by determining the lowest-cost next action for each step from episode start (no items on the table, subject at starting position) to task success (all required items on the table and – if specified – in the target position, subject standing in front of the table). If no specific table setup was required in the task statement, we assume all table setups (i.e., task solutions) to be equally good.

Each cost $C_{i,j}$ is calculated by determining the Euclidean distance (Eq. 1) between two item locations $i(x_1, y_1)$ and $j(x_2, y_2)$ in a 2D representation of the specific environment. This distance is further qualified by functional relations between items (parameter k) and reachability (parameter c) yielding a weighted cost computed as given in Eq. 2.

$$d(i, j) = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \quad (1)$$

$$C_{i,j} = d(i, j)^k \cdot c \quad (2)$$

Functional relations between items are defined as constraints that favor putting one item on the table earlier than a second item, e.g., because the first item is supposed to be placed below the second item (saucer and cup, placemat and plate, etc.) or because the item is used to define the place setting on the table (placemat, plate). Reachability indicates whether an item can be accessed directly or whether it is stored in a cupboard or the like which has to be opened first.

We assume functional relations between items to have an influence on the ordering of items since, with an ideal ordering, each item has to be picked up and placed on the table only once. In contrast to choosing an arbitrary ordering, in which items already on the table might have to be moved again (e.g., lifting the cup to place the saucer below it), this ideal sequence minimizes the physical effort. Since the opening of cupboards also involves physical effort, reachability is considered to be another cost factor. Parameters k and c are treated as free parameters of the model and will be estimated from the first considered dataset.

Each modeled environment consists of the corresponding spatial layout with item coordinates, the task description (required items), and constraints (how many items can be carried at once). Following a stepwise-optimal strategy, in each step the cost for all next possible actions is calculated (Eq. 2, i = current location, j = item location) and the item with the lowest associated cost is chosen to be picked up next (Fig. 1).

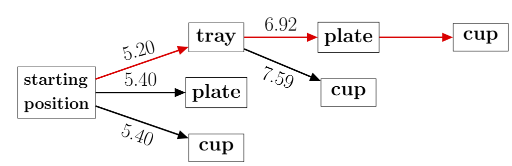

Figure 1: Example for stepwise-optimal item choosing based on weighted cost (TUM environment, k+c set)

To evaluate our model we test its ability to account for table setting across three datasets. On the first dataset, the TUM dataset, we estimate k and c and test whether a stepwise or a global optimality model provides a more appropriate explanation. The second dataset, the EPIC-KITCHENS dataset, was employed for testing our model's generalizability to additional individuals and additional environments. The third dataset, a self-collected virtual reality dataset, was employed to test a regionalization prediction arising from the model. All simulations compared variants of our model including only k, only c, including k and c, and neither including k nor c (default parameters).

TUM Dataset The TUM Kitchen Data Set (Tenorth, Bandouch, & Beetz, 2009) contains data from four subjects setting a table in different ways, each time using the same items in the same environment. Since the spatial properties of the environment and items did not change and the variance between observed sequences was low, we used the TUM dataset set to fit our model parameters, in the hope of obtaining a reliable estimate.

Each trial began with the subject facing the kitchen (standing between location A and B, see Fig. 2) and ended with all required items being on the table (at location C or D in the environment). The necessary items for table setting were stored in location A (tray, napkin), in the drawer between A and B (silverware), and B (plate, cup). Of the 20 video episodes, video 18 consists only in repetitive movement and had to be excluded from our analysis.[1] Variations include the location of the setup on the table and the number of items being transported at a time (one or two).

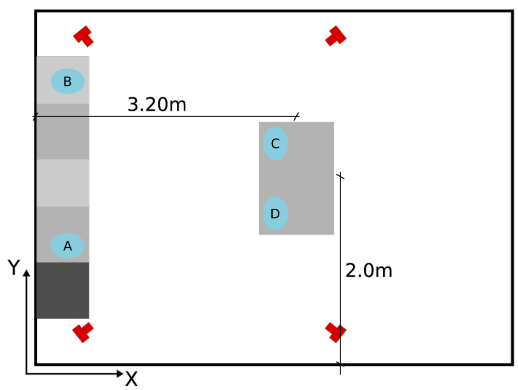

Figure 2: Layout of the TUM kitchen (Tenorth et al., 2009)

Method Parameters k and c were estimated by grid search. Parameter k was estimated per object (see Tab. 1) and c was estimated to be 1.2 for all objects in closed containers (e.g., cupboard, drawer). Setting parameter k to a value < 1.0 decreases the weighted cost, thus corresponding to a higher probability of taking the item in question first, whereas setting parameter c to a value > 1.0 increases the weighted cost.

$$DL_n = \frac{\text{edit distance}}{\text{maximum edit distance}} \quad (3)$$

To evaluate how well the model-generated and observed sequences matched, we computed the Damerau-Levenshtein distances (Damerau, 1964) and normalized by sequence length to make results comparable across sequences of different length. The resulting distance measure, DL_n, see Eq. 3, ranged from 0 (i.e., identical) to 1 (i.e., maximally different). As a baseline, mean edit distance was calculated for $n!$ samples generated without replacement for observed sequences of length n.

Results Comparing the edit distances between sequence predictions from the model and observed sequences (see Figure 3) clearly demonstrates that both factors have a strong influence on the order in which items are picked up and brought to the table (Fig. 3). Only when both factors are set, a match between predicted and observed sequences is achieved for

[1]For our analysis, the videos have been numbered consecutively, thus video 18 corresponds to video 19 (TUM numbering) and video 19 to video 20 (TUM numbering).

Table 1: Parameter estimates for different items

Item	**Value of k**
tray, placemat	0.9
plate (empty), napkin	0.95
all other items	1.0

nearly all episodes. This indicates that the decision which item(s) to get next does not rely on physical distance alone but is strongly influenced by the effort to retrieve or arrange items. Comparing model performances (default parameters, only one of both parameters or both parameters set, or globally optimal) using the Friedman test indicates a highly significant difference ($\chi^2(4) = 66.595$, $p < 0.001$).

To more specifically test the locality of strategies, we compared our stepwise-optimal to a globally optimal model (i.e., a model that plans ahead, determining the overall lowest-cost action ordering[2]). A Wilcoxon signed-rank test revealed that our model performs significantly better than the global model ($W = 0.000$, $p < 0.001$), which provides evidence for human behavior being locally optimal.

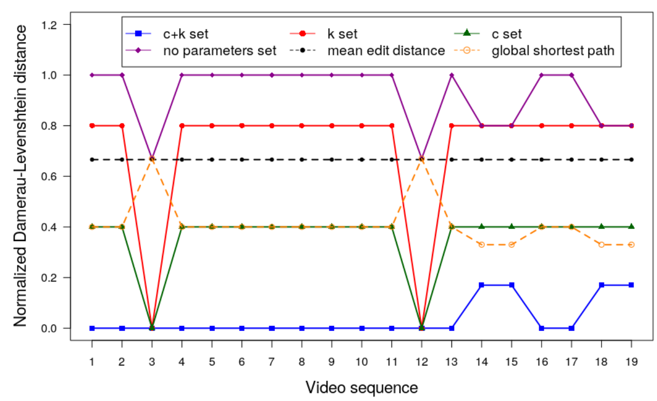

Figure 3: Model fit, TUM data

In order to validate the model, we verify its generalizability to other spatial environments and individuals using the EPIC-KITCHENS and a VR data set.

Model Generalizability

EPIC-KITCHENS

Data EPIC-KITCHENS (Damen, D. et al., 2018) is a large-scale first-person vision data set collected by 32 participants in their native kitchens. Since each participant recorded their activities in their home kitchen, spatial environments and items vary between participants, which makes this data set a strong generalization test of our model.

The participants recorded all their daily kitchen activities with a head-mounted GoPro (video and sound) for three consecutive days. Each recording starts with the participant en-

[2]Assuming each item is brought to the table first before picking up the next one.

tering the kitchen and stops before leaving the kitchen. The participants were asked to be in the kitchen alone, so that the videos capture only one-person activities. Each participant recorded several episodes.

The episodes contain a multitude of kitchen activities, such as cooking, stowing away groceries, and table setting. For the purpose of this analysis, we only used episodes with table setting actions, which reduced the sample size to 16 videos.[3]

Method Since the table setting actions are interleaved with cooking actions, specific items can fulfill different functions, such as a plate being used as container for a meal or as an empty (eating) plate. To account for such differences, items are not categorized according to item type but function (e.g. a plate not serving as the eating plate does not have strong functional relations as defined in factor k). For each predicted next item, the prior location was taken as a starting point, regardless of whether the corresponding action was a table setting action.

Results While the model prediction with default parameters (c = 1.0, k = 1.0) tends to be near to or worse than the baseline prediction (mean edit distance from $n!$ samples for each observed sequence of length n), with both parameters set we achieve better results than the baseline for nearly all episodes (Fig. 4). c and k improve prediction for most sequences even when only one factor is set (see first column of Tab. 2: $p < 0.05$ for both comparisons). While prediction accuracies show a significant difference for only c vs. both parameters set, model simulations with only k vs. both parameters set show no significant difference, indicating that k may be the decisive parameter considering the EPIC-KITCHENS dataset (see second column Tab. 2).

Overall, our model generalizes well to new spatial environments and individuals, which supports the model's key assumptions: stepwise optimality minimizing effort is subject to functional constraints and reachability. Comparing the performance of the model with both vs. default parameters set indicates a significant improvement of prediction accuracies with parameters (W = 0.000, p = 0.002), corroborating our assumptions.

Table 2: Wilcoxon signed-rank test comparing prediction accuracies of model simulations

	default parameters set (c = 1.0, k = 1.0)	$c + k$ set
c set, k = 1.0	$W = 0.000$ $p = 0.027$	$W = 0.000$ $p = 0.018$
k set, c = 1.0	$W = 0.000$ $p = 0.003$	$W = 0.000$ $p = 0.180$

[3]P01_01, P01_03, P01_05, P01_09, P10_01, P12_01, P12_06, P21_01, P21_03, P21_04, P22_12, P22_16, P24_02, P24_04, P24_05, P26_11. Videos have been numbered consecutively in our analysis.

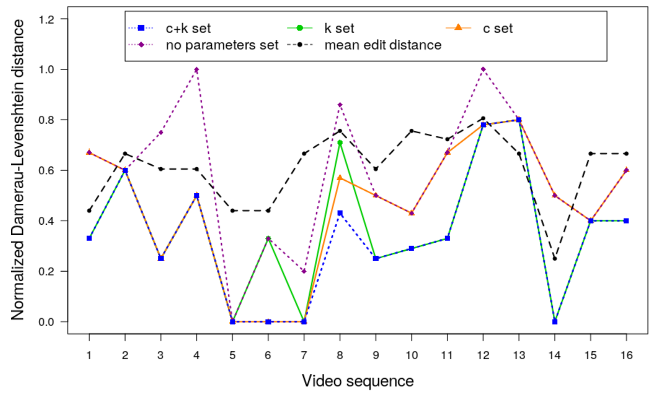

Figure 4: Model fit, EPIC data

Virtual Reality Data

One prediction arising from our model is that, whenever possible, people should tend to pick objects by regions, because this minimizes the physical effort related to traversing the distance between items. This idea receives first support from the TUM dataset: Videos 3 and 12, the only sequences in which two items can be picked up at once, show a bias towards regionalization, i.e., items stored in the same location are always picked up together (tray and napkin from location A, plate and cup from location B, Fig. 2).

To investigate this prediction in more detail, we analyze the presence of such regionalization in our third data set. The study was conducted in a virtual environment because this provides exact movement trajectory and distance measurements and allows for more control over the environment than a (possibly noisy) real-world setting. At the same time, the VR environment promises higher ecological validity than a laboratory setting.

Data The data contains table setting sequences in a VR environment from a single participant, who was naïve with respect to the purpose of the experiment. The virtual kitchen consisted of three separate regions (fridge, tray area, island area; Fig. 5), each of which had to be visited at least once.

The fridge contained a number of dairy products and orange juice, drawer 1 silverware, drawer 2 mugs and glasses, drawer 3 bowls, and the cupboard a number of food packages such as cereal. The participant moved through the virtual environment by moving through a corresponding but open physical space, experiencing the virtual environment through a HTV Vive head-mounted display. Movement was tracked via the head-mounted display while interaction with the environment was realized through two HTC Vive controllers (one in each hand).

The participant was asked to set the table for one person having breakfast. The minimum set of items consisted of a cereal bowl, a spoon, cereal, milk, a glass, and juice; additional items could be added by the participant if desired. The task was to first assemble all necessary items on the tray and then to carry the items to and distribute them on the table. The participant was familiar with the kitchen and knew the location of all required items well. Data from 39 trials was collected. For action orderings we considered the order in which items were grasped and put on the tray.

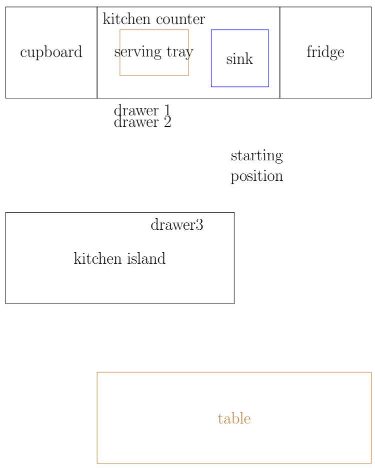

Figure 5: Layout of the Virtual Reality kitchen

Results We observed a strong preference for regionalized item collection and for choosing the order based on those regions and the distances between them: Items from the same region were picked up jointly and the regions were traversed in an order that minimized the overall walking distance.

The prediction of the model being verified, we further tested it by applying it to the Virtual Reality data set (Fig. 6). In doing so, k could not be set because the items were assembled on a tray first, rendering constraints due to functional relations between items irrelevant. Moreover, c had no influence, because all items were stored in cupboards, drawers, or the fridge. Without both factors, the model still performs better than the baseline (i.e., mean edit distance, calculated as described above), further corroborating that human treatment of weakly constrained action sequences is to no small part governed by stepwise optimization of traveled distance.

These results also show the limitations of the model: While functional relations and reachability appear to be important factors in everyday action sequences, they explain only part of the variance in the observed sequences. For example, relying only on physical (2D) distance, the model is not able to distinguish between items stored in the same location and can thus only predict the next best region in such instances.

Conclusion and Future Work

Our results suggest that action orderings in everyday activity result from stepwise-optimization, aiming to minimize cognitive and physical effort by factoring in properties of the spatial environment. When dealing with weakly constrained action sequences, the ordering of actions is not chosen arbitrarily but according to preferences, which take distance, functional relations between items, and reachability into account in order to minimize the overall effort. These findings are consistent with the theories of external scaffolding and strong spatial cognition, i.e., humans using properties of the environment to their advantage.

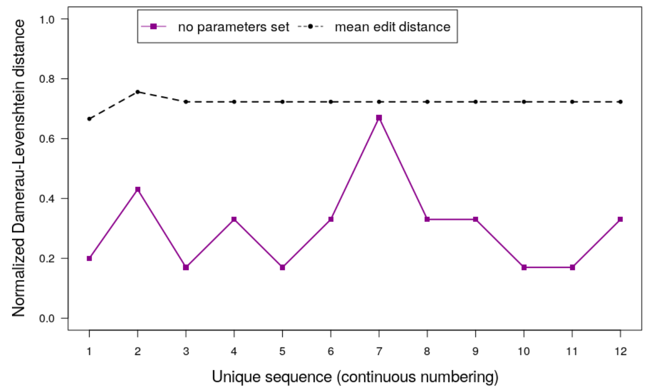

Figure 6: Model fit, Virtual Reality data

Our contribution also touches on the question whether human cognition and behavior is best seen as globally or locally optimal. Our comparison of models realizing these two types of optimality indicates that human behavior in everyday activities can indeed – as proposed by adaptive rationality – better be explained by a locally optimal strategy, tuned to maximize performance by following a stepwise-optimal heuristic. We expect our proposed stepwise-optimal model not to be specific to the activity of table setting, but to be generalizable to other everyday tasks. While functional relations may be task-specific, i.e, depend on how the necessary items are used in a given task and how this affects the functional relations between them, we assume all model parameters to represent important constraints also for other everyday activities.

The success of the stepwise-optimal model also raises interesting questions regarding the control of action sequences. In existing models of control of sequential actions (e.g., Cooper, Ruh, & Mareschal, 2014; Botvinick & Plaut, 2004), the assumption seems to be that the to be controlled sequence is completely known from the outset. But how are action sequences controlled, which are, as suggested by our work, not completely known before execution? Do the same control mechanisms apply or can they be adapted?

In the current model, the representation of task environments and distances is represented only in 2D. A 3D model could potentially show other important factors, e.g. whether picking up items from very high or low storage location is considered more effortful. This might also allow the model to better predict the next lowest-cost item when multiple items are stored in the same (2D) location. Cognitive effort is another important factor that needs to be considered in future versions of the model, since minimization of effort is assumed to affect both physical and cognitive effort.

While our model with the chosen constraints fits well to the data and is able to explain variability between datasets, other, yet unknown factors may be of importance in determining human behavior in everyday activities. Future research is therefore needed to uncover other relevant mechanisms underlying spatial cognition in everyday tasks and to explore how these interact with our proposed constraints.

Future work also needs to investigate whether using a heuristic model can be interpreted as opportunistic behavior and to clarify the relation between traversed overall distance and required time in the context of effort minimization.

Acknowledgments

The research reported in this paper has been supported by the German Research Foundation DFG, as part of Collaborative Research Center (Sonderforschungsbereich) 1320 "EASE - Everyday Activity Science and Engineering", University of Bremen (http://www.ease-crc.org/). The research was conducted in subproject P03 "Spatial Reasoning in Everyday Activity".

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