What Everyday Activities Reveal About Spatial Representation and Planning Depth

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Abstract

Successfully performing everyday activities such as loading the dishwasher or setting the table relies on the involvement of many cognitive abilities. As such, everyday activities provide a unique window for investigating the involved cognitive abilities as well as their interaction, promising high ecological validity of the obtained findings. Against this background we investigated two cognitive abilities and their combination, which are crucial for virtually all everyday activities. Specifically, we investigated the nature of mental spatial representation and planning depth in rational planning by analyzing table setting behavior across many environments and actors. As recent modeling work indicates that rational planning is influenced by spatial properties of the environment, we investigate how representation of and reasoning about the spatial environment impact sequential action planning. Using a modeling approach, we compare models implementing different plannings depths and differently complex spatial representations. Our findings indicate that people plan opportunistically (one step ahead) and rely on a two-dimensional representation of their environment. These findings lend credit to the idea that humans minimize their cognitive effort (simpler representations, shallow planning) to efficiently perform everyday tasks.

Keywords: spatial cognition; rational planning; action sequences

Introduction

Everyday activities, such as cooking, cleaning, or setting a table, seem simple, but are in fact highly complex tasks involving many different cognitive abilities. Setting the table, for example, requires action and motor planning, navigation, spatial memory, action and motor control, and error monitoring and correction, among others.

We argue that everyday activities provide a unique and instrumental window for investigating the involved cognitive abilities. For one, everyday activities constitute *complex tasks* in the sense of Newell (1973) such that their study promises not only a deeper understanding of each of the abilities, but also of their interaction and integration. Furthermore, findings obtained from investigating everyday activities arguably offer higher ecological validity than findings obtained from experimental tasks commonly employed in the Cognitive Sciences. At the same time, everyday activities are still simple enough to also be investigated in the lab. Last but not least, understanding cognitive abilities in everyday activities is of great applied relevance by potentially allowing to better support people to live independently (e.g., in old age) without requiring professional aid.

Against this background, in this contribution, we investigate the nature of mental spatial representation and planning depth in rational planning by analyzing everyday activities. Planning and control of action sequences are necessary requirements for successful task performance in everyday life. In existing models of sequential action control (e.g. Botvinick & Plaut, 2004; Cooper & Shallice, 2006), the assumption seems to be that the to be controlled sequence is completely known from the outset, whereas we propose a stepwise approach. Recent modeling work suggests that rational planning is influenced by spatial properties of the environment, taking distance, relational dependencies (strong spatial cognition), and topology (containment) into account (Wenzl & Schultheis, 2020). Building on this modeling work, we examine how many dimensions people take into account when representing and reasoning about their spatial environment as well as how many steps ahead they plan their actions (i.e., planning depth). Our investigations take the form of a model comparison study, in which we develop and compare models realizing different dimensionalities of spatial representations and planning depths. The models are compared across three datasets of human table setting activities comprising various actors and environments. Modeling results indicate that people plan opportunistically employing a single-step look-ahead and that they rely on a two-dimensional representation of the environment, largely ignoring the vertical dimension.

The remainder of this paper is structured as follows: First, we give an overview of the role of rational planning, space, and minimization of cognitive and physical effort in the context of everyday activities. Subsequently, we investigate the role of planning depth and dimensionality of spatial representation using a modeling approach. We conclude with a discussion of our results and issues for future research.

Rational Planning, Space, and Minimization of Effort

Rational Planning

Mechanisms such as knowledge representation and cognitive processes have to be taken into account when trying to explain human behavior through rational analysis (Jones & Love, 2011). This is the core assumption of *bounded rationality* (Simon, 1955) which takes limitations in knowledge and processing capacity into account. To identify effective mechanisms that can plausibly be implemented by a resource-bounded human brain, computational modeling has been shown to offer a useful analysis tool (Icard, 2018).

Adaptive rationality proposes 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). Human cognition generally is assumed to be locally optimal. This is consistent with research on sequential information search and planning which indicates that humans tend to use heuristic stepwise-optimal strategies rather than planning ahead (Meder, Nelson, Jones, & Ruggeri, 2019).

Taking the limitations of the human mind and the complexity of everyday activities into account, we propose that humans deal with such activities by using a rational planning strategy to choose their next action.

Space

All human activity takes place in space: Required items for a given (everyday) activity are located in the physical environment, and movement within this environment is necessary to perform the activity. Spatial properties, e.g., distance, are directly related to the required physical effort. While choosing the action sequence for performing a specific activity, the spatial properties of the environment may impose constraints, such as having to move one object first before being able to reach another object located behind it. Even if there are no hard constraints there are a number of reasons to believe that the order of action sequences is influenced by the spatial environment and its mental representation.

First, the organization of objects in physical space aims to minimize cognitive effort and to facilitate the performance of everyday activities (Kirsh, 1995). 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 behavioral strategies relying on strong spatial cognition (van de Ven, Fukuda, Schultheis, Freksa, & Barkowsky, 2018) and cognitive offloading (Clark, 1996; Wilson, 2002) (see Minimization of Effort). Second, previous research has shown that the nature of mental representations of space has a marked influence on peoples behavior. Three-dimensional spaces seem to be represented in a "bicoded" way, splitting the representation in a metric planar representation of the plane of locomotion and a separate, possibly non-metric representation of the orthogonal space (Jeffery, Jovalekic, Verriotis, & Hayman, 2013). Human spatial navigation performance is significantly worse when navigating in a vertical environment than in a horizontal environment (Zwergal et al., 2016) and distance is represented with higher accuracy along the horizontal than the vertical axis (Hinterecker et al., 2018).

Taking the above considerations into account, we assume spatial properties of the task environment, i.e., distance, functional dependencies, and topology to be important factors when deciding for the next action.

Minimization of Effort

Hull's *"law of less work"* (Hull, 1943) states that physical effort tends to be avoided. Newer research indicates that physical and mental effort are equally aversive (Kool, McGuire, Rosen, & Botvinick, 2010). The concept of an internal cost of cognitive effort allows to explain the (globally) suboptimal strategies frequently observed in humans, as favoring simplifying strategies (heuristics) can be subjectively optimal when reducing the internal cost of mental effort outweighs the benefit of a more accurate strategy.

External scaffolding is a possible strategy to reduce cognitive effort (Clark, 1996). Accordingly, external structures are used to facilitate human problem-solving and to reduce the cognitive effort of a specific task by offloading (part of) the problem solution to external scaffolds such as tools or memory aids. Strategies to offload cognition are used particularly often in the context of spatial tasks (Wilson, 2002) (see Space).

Against this background, we assume that humans prefer planning strategies that locally minimize the effort required for task success.

Rational Planning Model for Table Setting

Consistent with the spatial environment being used to facilitate task performance, i.e., intelligent use of space (Kirsh, 1995), external scaffolding (Clark, 1996; Wilson, 2002), strong spatial cognition (van de Ven et al., 2018), and mental representation of space (Hinterecker et al., 2018), we expect specific spatial constraints to be of importance for planning.

Based on previous research evidencing that humans favor 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 the control of routine sequential actions, such as table setting, follows a strategy of rational planning. Taking the role of spatial properties in everyday activities into account, we propose that humans prefer specific 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.

Employing a modeling approach, we examine the influence of the following spatial aspects of the task environment on action organization during table setting:

- *Distance*: minimizing traversed distance,
- *relational dependencies*: e.g., 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
- *topology (containment)*: picking up items from, e.g., a counter top, is considered less effortful than picking up items stored in a closed cupboard.

We implemented our core assumptions in a computational model. The model approximates rational planning 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).

Each cost $C_{p,q}$ is calculated by determining the Euclidean distance between two item locations $p(x_1, y_1, z_1)$ and $q(x_2, y_2, z_2)$ in a nD representation of the specific environment, where n is either 1, 2, or 3. This distance is further qualified by relational dependencies (parameter k) and containment (parameter c) yielding a weighted cost computed as given in Eq. 1, where d is the Euclidean distance. 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.

$$C_{p,q} = d(p,q)^k \cdot c \tag{1}$$

Relational dependencies 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, etc.) or because the item is used to define the place setting on the table (placemat, plate). Containment 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 relational dependencies to have an influence on the ordering of items as, with an ideal ordering, each item has to be picked up and placed on the table only once, and the placement of subsequent items is facilitated (e.g., not having to know how much space to leave between items of silverware for the plate). 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, or making space for the plate by moving the silverware), this ideal sequence minimizes the cognitive and physical effort. Since the opening of cupboards involves physical effort, containment is considered to be another cost factor. The weighted cost for each possible item also depends on which dimensions are considered when calculating the cost: Distances differ depending on whether they are computed in 1D (i.e., with respect to the x, y, or z axis), 2D (i.e., with respect to the xy, xz, or yz axes), or 3D (i.e., with respect to the xyz axes). Parameters k and c are treated as free parameters of the model and will be estimated from the data.

Simulations

Simulations aim to test two specific aspects: Planning depth and dimensionality. For this purpose, we conducted two model comparison studies: The purpose of the first simulation was to compare different levels of planning depth: whether the model assumes a one- or a two-step look-ahead (see Planning Depth). The second simulation examined the dimensionality of the spatial representation people employed for distance calculations (see Dimensionality).

Based on a given spatial layout with item coordinates, the task description (required items), and a sequence of current

Table 1: Parameter estimates for different items

Category of relational dependencies (k)	Items
strong	tray, placemat, table cloth
medium	plate (empty), napkin
none ($k = 1$)	all other items

locations, simulations were conducted as follows: For each predicted next item, the prior location was taken as the current location, regardless of whether the corresponding action was a table setting action. In each step the cost for all next possible actions was calculated (Eq. 1, p = current location, q = item location), from which the item with the lowest associated cost was chosen to be picked up next (Fig. 1). If there were multiple items with the same associated cost, one item was chosen randomly.

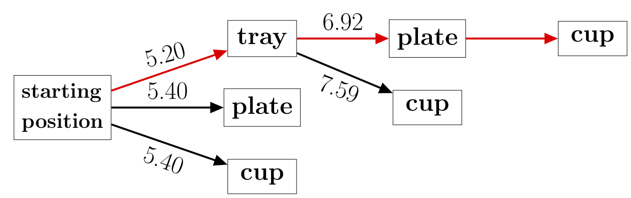

Figure 1: Example for stepwise-optimal item selection based on weighted cost (TUM environment, k and c set)

Parameters k and c were estimated by grid search. Parameter k was estimated per item category (see Tab. 1), i.e., items with strong relational dependencies (e.g., placemat), items with medium-strength relational dependencies (e.g., plate) and items without relational dependencies ($k = 1$). c was estimated for all objects in closed containers (e.g., cupboard, drawer). To evaluate how well the sequences generated by the model and the observed sequences matched, we computed the Damerau-Levenshtein edit 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. 2, 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 and averaged over all sequences. For each parameter combination, model-generated and observed sequences were compared for $n = 100$ iterations, considering the median edit distance over all iterations.

$$DL_n = \frac{\text{edit distance}}{\text{maximum edit distance}} \tag{2}$$

Using a modeling approach, we investigated planning depth and dimensionality across three table setting datasets (Sec. Data). We estimated k and c by finding the best-fitting model over all unique sequences of action orderings. Values for (strong) k were tested in a range between 0.1 and 0.8 (including ending values), with medium-strength k defined as

$k + 0.1$ and steps of 0.1. Parameter c was tested in the range between 1.1 and 1.9 (including ending values), with steps of 0.1.

Data

TUM Kitchen 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. 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). 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). The x axis represented the traversable space between table and storage locations (cupboards, drawers) as well as kitchen appliances (stove, fridge), while the y axis represented the axis of movement along storage locations and kitchen appliances (fridge, cupboard, stove, etc., see Fig. 2). Of the 20 video episodes, video 18 consists only in repetitive movement and had to be excluded from our analysis.

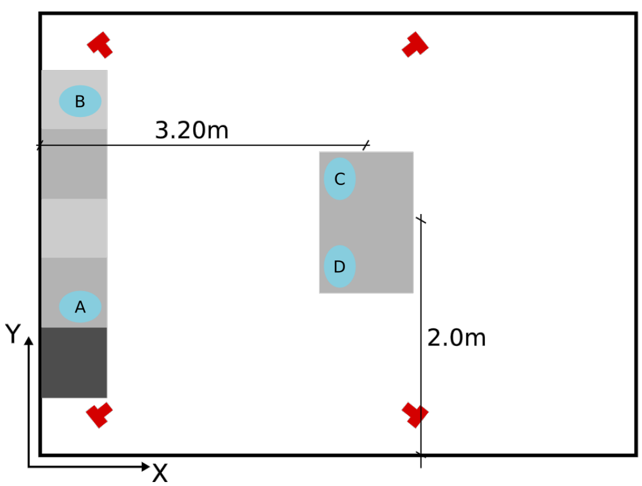

Figure 2: Layout of the TUM kitchen (Tenorth et al., 2009)

EPIC-KITCHENS EPIC-KITCHENS (Damen 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.

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 entering 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.[1]

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 is not considered to have strong relational dependencies as defined in factor k).

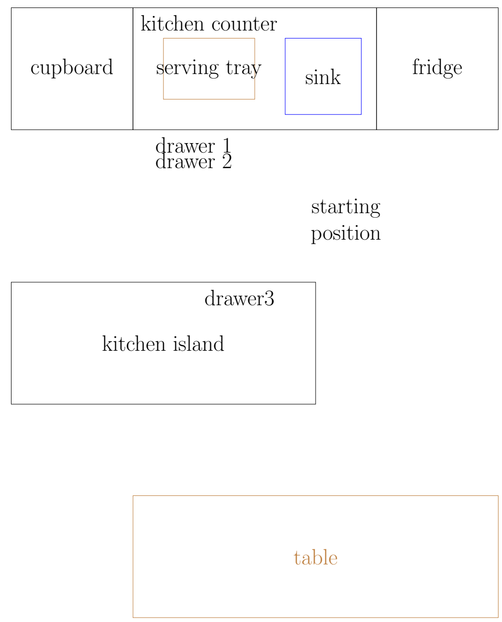

Figure 3: Layout of the Virtual Reality kitchen

Virtual Reality Dataset The data contains table setting sequences in a VR environment from a single participant.The virtual kitchen consisted of three separate regions (fridge, tray area, island area; Fig. 3), 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 HTC 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 (cereal bowl, spoon, cereal, milk, glass, juice) could be expanded by the participant if desired. The task was to first assemble all necessary items on the tray and then to carry the items to the table. The participant was familiar with the kitchen and knew

[1] 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.

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.

Model Comparisons

Planning Depth

We ran model simulations for one and two steps of planning ahead (Fig. 4). The one-step model works as described above. The two-step model works as follows: after choosing a first item, a second item is already chosen while picking up the first item, based on the same weighted cost calculation as before. The second item is then picked up next regardless of whether it is the lowest-cost item for the next starting point, repeating this process until task completion. Because both models have the same number of parameters, functional form, and draw on identical sample sizes, a goodness of fit measure is equivalent to more complex measures of generalizability (Pitt & Myung, 2002). Accordingly, we considered and report goodness of fit measures for comparing the models.

Both models consider a 3D environment for distance calculation (see Eq. 1). The best fit for the one-step model is achieved for parameters strong $k = 0.6$, medium $k = 0.7$, and $c = 1.9$, which yield an average edit distance of 0.411 (median: 0.4). The best fit for the two-step model is achieved for parameters strong $k = 0.5$, medium $k = 0.6$, and $c = 1.2$, which yield an average edit distance of 0.415 (median: 0.4). Both results are lower than the baseline of 0.603 (see Simulations).

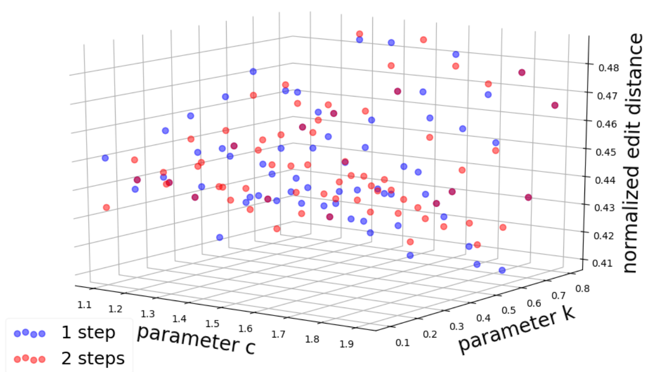

Figure 4: Model fit based on planning depth (k = strong k)

Although the models differ in the action orders they generate, they seem to perform similarly well in accounting for human behavior (Fig. 4). To further investigate, we computed the average edit distances across all possible parameter value combinations. Again, models performed very similar (1 step: 0.446, 2 steps: 0.446, median for both: 0.4) and comparing their prediction accuracy using the Wilcoxon signed rank test shows no significant difference ($W = 831.500$, $p = 0.686$).

As cognitive offloading tends to be used particularly often in spatial tasks (Wilson, 2002), we argue that the results indicate that people plan only one step ahead, as the process of remembering the second item to be picked up can be considered cognitively effortful and adding a second step does not achieve a better fit between predicted and observed behavior.

Dimensionality

To assess dimensionality, we compared seven models that assumed spatial representations along the x, y, z, xy, xz, yz, xyz axes, respectively, all of which assumed one-step planning. For the same reasons as with the depth model comparison, we again used goodness of fit as comparison measure.

Prediction accuracies for the first simulation show a highly significant difference ($\chi^2(6) = 507.748$, $p < 0.001$), which lends support to the idea that dimensionality has a strong influence on action organization in everyday activities. Since previous research shows a preference for 2D spatial representation and better navigation performance in 2D environments, we assume that calculating distances in 2D instead of 3D might reduce the necessary cognitive effort.

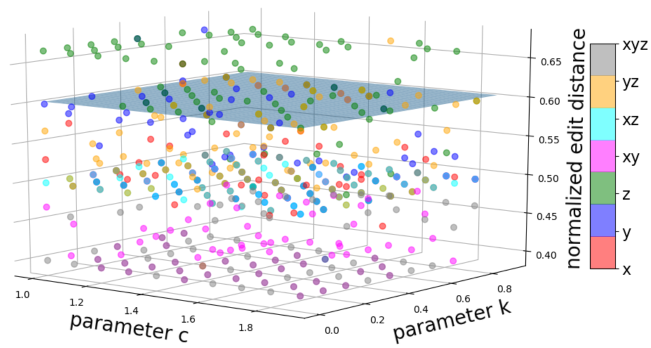

Figure 5: Model fit based on dimensionality (k = strong k)

The distribution shows that the average edit distance between model-generated and observed sequences is lowest when considering xy or xyz for dimensionality (Fig. 5, baseline shown as plane), with xy achieving slightly better results (0.438 vs. 0.444, averaged over all possible parameter combinations; median for both 0.4). In a pairwise comparison of model simulations based on xy and xyz spatial representations using the Wilcoxon signed rank test, the model results considering a horizontal versus a horizontal and vertical spatial representation also differ significantly ($W = 1561.000$, $p = 0.05$), indicating that people seem to ignore the vertical dimension.

As the importance of single (1D) axes might be dependent on how much they can influence the calculation of physical distance, i.e., the actual possible movement span, we compared the span for each axis (x, y, z). y has the highest average span: 3.17 vs. 1.89 and 1.833 for x and z, respectively. The average edit distance and the average volume of all task environments show a strong negative correlation ($\rho = -0.708$, $p < 0.001$), i.e., with decreasing volume/span of the task environment, the prediction error increases (Fig. 6).

In order to account for the possibility that people assign different importance to the individual spatial axes dependent on their span width, we ran a second simulation of the model

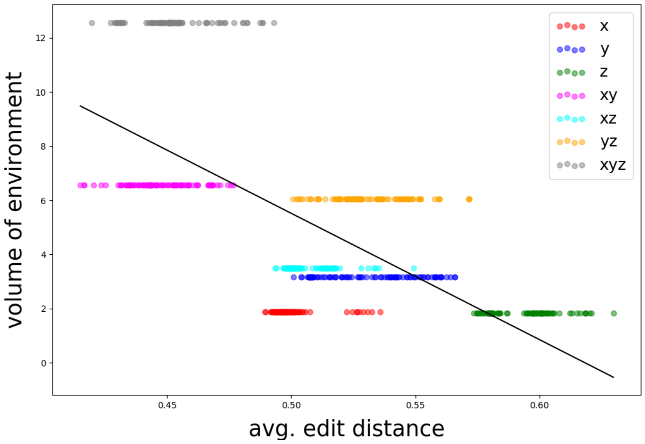

Figure 6: Correlation between average edit distance and volume/span of task environments for each spatial representation

that incorporated a weight criterion for each axis. We calculated a weighted Euclidean distance between item locations by multiplying the partial difference for each axis as shown in Eq. 3, where the axis weight w_n was defined as in Eq. 4. Assuming an environment with axes spans $x = 3$, $y = 2$ and $z = 1$, this results in $w_x = 0.5$, $w_y = \frac{1}{3}$, and $w_z = \frac{1}{6}$.

$$d(p,q) = \sqrt{(p_x - q_x)^2 \cdot w_x + (p_y - q_y)^2 \cdot w_y + (p_z - q_z)^2 \cdot w_z} \tag{3}$$

$$w_x = \frac{span_x}{span_x + span_y + span_z} \tag{4}$$

In the new model, z still shows the highest error rate in prediction (0.60 average edit distance, thus similar to the baseline), whereas xyz achieves a slightly better fit, but still has a higher average edit distance than xy (xyz: 0.510, xy: 0.514; median: 0.51 for both). Comparing two- and three-dimensional representation using the Wilcoxon signed rank test indicates a significant difference ($W = 1348.000$, $p = 0.005$), i.e., xy achieves the best fit in both model variations.

Conclusion and Future Work

Our results lend to support to our initial argument of the merits of investigating cognitive abilities by analyzing everyday activities. Our analyses of table setting provided two main findings: First, people behave consistently with a model that plans one step ahead and, second, a representation of two-dimensional horizontal space seems to be preferred over a three-dimensional representation including the vertical.

Both findings indicate that the cognitive costs of alternative planning strategies and representation structures outweigh their potential benefits. These findings are consistent with previous research showing human navigation performance to be better in 2D environments (Zwergal et al., 2016), differences in the accuracy of distance encoding in horizontal vs. vertical space (Hinterecker et al., 2018), and the theories of external scaffolding and cognitive offloading, i.e., humans using properties of the environment to their advantage.

We expect our proposed planning model not to be specific to the task of table setting, but to be generalizable to other everyday activities as well. Aspects to consider in future models are possible interdependency effects between planning depth and dimensionality, as well as cognitive effort. While we consider cognitive effort in the scope of relational dependencies and dimensionality, further research is needed on how cognitive effort impacts everyday activities.

As the model is not able to provide reliable predictions for sequences with low variance in the considered constraints (e.g., similar distances, no relational dependencies between items or containment), other potentially influential factors need to be investigated further and addressed in future versions.

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