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Human-like Prototypes for Psychologically Inspired Knowledge Representation

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Abstract

We evaluate human grouping of everyday objects for a psychologically inspired knowledge representation based on prototype theory, named prototype-based knowledge representation (ProKRep). Our overall aim is to develop a knowledge representation system that one day could be used by kitchen robots. We conducted a study in which participants had to sort different kitchen objects into a digital kitchen. We chose a kitchen as a use case, since people have to tidy up dishes every day. We identified object groups whenever at least half of the participants put two items on the same shelf. Out of these categories we calculated the respective prototype. We then tested the similarities of all categories to all prototypes, which turned out to be reasonable.

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1 Introduction

In our aging society household robots are becoming more and more important. In order to ensure a satisfying human-robot interaction, it is necessary that the robot finds human-like, flexible solutions to everyday problems. Human knowledge representation is characterized by a high degree of ambiguity and situation-specific adaptation. A spoon is at the same time a tool for eating and a measuring device for cooking; when we have flowers but not a vase, we use a drinking glass or some other geometrically suitable container. When machines interact with people, they should show the same flexibility of interpreting and using objects. An example application underlying our present work is a household robot that should be able to arrange objects in a kitchen in such a way that users can intuitively find them without being told. For example, after a relocation, or simply tidying up dishes that have been in the dishwasher. A

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second application could be, as mentioned, to find similar objects if the desired one, e.g. a vase, is missing [12].
In previous work, we have proposed a mathematical formalized prototype-based knowledge representation [17] that is based on a model from psychology [14, 11]. The model was validated qualitatively with a set of dishes, where predefined object categories containing these dishes were used to create prototypes. We could show that this model provides the desired flexibility needed by robots interacting with humans.

Beside our approach there are other feature-based paradigms in knowledge representation: for example, the exemplar-based model [9]. In oder to categorize objects they are compared to all stored *exemplars* that have already been classified [10]. Further, there are systems like Dual PECCS using hybrid representations named *heterogeneous proxytypes*, which combine prototype- and exemplar-based representations [8, 7, 13]. An alternative approach to object replacement is described by Olteţeanu and Falomir [12]. They consider objects similar if they have at least one common feature, for example, the shape. Besides connectionist models and artificial neural networks [7], logic-based paradigms constitute another approach. Ontologies, for example, are able to store a wide range of everyday knowledge and they work well with automatic reasoning techniques [6, 16]. Ontology classifications, however, are unambiguous: an object either belongs to a category or not and reasoning gives definite answers. One application of an ontology is *Taaable*, a Case-Based Reasoning system that uses a recipe book as a case base to answer cooking queries [1, 2, 3]. They utilize an ontology to represent ingredients.

In our opinion, for interacting with people, a machine should contain a representation of prototypes that is similar to the prototypes used by users. Our goal was to create realistic prototype representations for the specific, everyday task of arranging objects in a kitchen. To this end, we conducted a study, in which participants had to stow away a set of given objects in a simulated kitchen. From the observations of the study, we calculated categories of objects. These categories represent things that are somehow considered as being similar in the context of the given task. For each category we calculated a prototype from the object properties in the category, thus building an abstracted model of kitchen objects. To test this model we averaged over the similarities of all objects of each category to each prototype.

2 The Kitchen Study

We conducted the study in a kitchen simulation that represents kitchen shelves, drawers and typical kitchen objects. We used a kitchen simulation instead of a mere grouping experiment, because we wanted to simulate some real aspects of a kitchen like having wall cupboards and a stove amongst others. But also having some constraints, e.g. the size of cupboards. Users drag-and-drop 134 objects – frequent objects like cutlery and plates had been multiplied – into the shelves (Fig. 1). The kitchen simulation is a web application but the study was done offline and every participant used the same laptop computer. An investigator was always present, but did not answer any questions except questions regarding the handling of the web application. The goal was to distribute the objects onto the cupboard shelves just as you would do if you were organizing a new kitchen. There was no time limit to the study and each participant received the same written instructions. The 23 participants (12 female), aged between 22 and 65 years (M = 38.7 years, SD = 16.61 years), were recruited among students from the University of Tübingen, acquaintances, family and friends. They received no reward and all gave informed consent.

Figure 1: Screenshot of the kitchen simulation. Pictures: Nico Reichenthaler and Stefanie Müller

Category	**Identified items constituting one category**
1	5x tumbler
2	5x cup
3	5x beer mug
4	broth, onion, chocolate, oil, vinegar, juice
5	can opener, corkscrew, soup ladle, egg whip, scissors, salad servers, spatula01, spatula02, pliers for pasta, small kitchen knife, potato peeler, big kitchen knife, bottle opener, 5x fork, 5x knife, 5x spoon
6	tea towel, pot cloth, tablecloth, napkins,
7	big pan, small pan, big pot, small pot
8	5x big bowl, 5x small bowl
9	5x big plate, 5x soup plate, 5x small plate
10	coffee machine, electric kettle, toaster
11	5x salad bowl
12	5x schnapps glass, 5x waterglass
13	5x champagne glass, 5x wine glass
14	5x soup bowl with 2 handles
15	5x teacup with a trivet
standalones	coffeepot, cake pan, measuring jug, chopping board, platter, sieve, soup tureen, tray, teapot, thermos jug, drinking bottle, Tupperware, vase, wok

Table 1: Object categories identified in the kitchen study

The row "standalones" contains all items that could not be identified as members of a category. That is to say, those have been stowed by the subjects too differently.

3 Identification of Categories and Prototypes

We calculated an overall similarity matrix M [5, 4] of all 134 objects for all participants. We defined an equivalence relation $o_1 \sim o_2$ between two objects if object o_1 was put into the same shelf as o_2 by at least half the participants (i.e. if the entry $M(o_1, o_2) \geq 11$). The equivalence classes [18] defined by this relation are our object categories (Tab. 1).

We considered several features of the kitchen objects (Tab. 2). We measured these features for each kitchen object. Since we had ten different sorts of material (Tab. 2) we gave them values between one and ten. The prototypes contained the most frequent material occurring in its own category. If there had been more than one "most frequent" material, we incorporated both in the prototype.

	height [cm]	width [cm]	depth [cm]	charge [l]	# handles	inner depth [cm]	material
prototype 1	11.0	7.3	7.3	0.3	0.0	10.8	4
prototype 2	11.0	8.0	12.0	0.3	1.0	10.5	8
prototype 3	28.3	8.0	12.2	0.8	1.0	27.2	1
prototype 4	15.8	10.2	9.4	0.2	0.0	13.6	2
prototype 5	2.3	4.7	22.4	0.0	0.0	0.8	5
prototype 6	2.7	18.6	25.6	0.0	0.0	0.0	3
prototype 7	8.6	32.3	29.9	2.6	1.3	7.6	{6, 9}
prototype 8	8.4	15.5	15.5	0.8	0.0	7.0	8
prototype 9	2.6	23.5	23.5	0.3	0.0	1.2	8
prototype 10	26.5	20.4	17.7	0.7	0.3	8.3	4
prototype 11	4.3	14.0	14.0	0.3	0.0	4.0	1
prototype 12	7.3	4.5	4.5	0.1	0.0	6.3	1
prototype 13	17.5	6.4	6.4	0.2	0.0	9.9	1
prototype 14	5.5	17.0	11.8	0.4	2.0	5.0	8
prototype 15	7.5	11.5	8.7	0.2	1.0	7.0	8

Table 2: Prototypes

Averaging over all items of an identified category (Tab. 1) gave us the prototypes. The inner depth of an object was the amount of concavity. We defined the materials in the following way: glass = 1, food = 2, tissue = 3, plastic = 4, stainless steel = 5, Teflon™= 6, wood = 7, china = 8, enamel = 9, and iron sheet = 10.

4 Validation

In order to evaluate if our approach ProKRep is reasonable, we calculated a distance measure between all items and all prototypes. Out of those we further calculated the similarities according to [15, 11, 17]. For all attributes, except the material, we calculated the normalized psychological distance d_{xP_C} between an item $\mathbf{x}$ and a prototype $\mathbf{P}_C$ of a specific category C as follows: $d_{xP_C} = \sum_{i=1}^{N_a} w_i \frac{|x_i - P_{C_i}|}{s_{C_i}}$, where w_i is the weight of the attribute i of N_a attributes. P_{C_i} is the prototype of a certain attribute in a specific category and s_{C_i} the standard deviation [17]. Since we did not measure any classificatory significance of the features, we set all weights to the same value (1/7) in the first validation. In the case of the attribute *material*, we set the distance to one, whenever there was a mismatch, and zero otherwise.

Averaging over the similarities of all items – constituting a category – to all prototypes showed best matches of the categories to their own prototype (Tab. 3). One can see, that the averaged similarities are greatest where they match their prototype, that is on the diagonal. There is only one exception in prototype four, which was constituted out of items having as feature *material* the value `food`.

5 Discussion and Conclusion

The mismatch of the averaged similarities of category four (*food*), could be because in the case of food, geometric dimensions seem to be completely irrelevant. Since we only had six groceries, subjects might have just wanted to sort these together. When we set all weights to 0.05, but the weight for *material* to 0.7, this effect vanished and the averaged similarities of category *four* to their own prototype became largest. This goes along with the statement by Olteţeanu and Falomir: the feature of material plays an important role in the object domain [12].

We showed that our approach of a prototype-based knowledge representation is reasonable in that, that items are most similar to their own prototype, as they are supposed to be. So with this work we provide a proof-of-concept of ProKRep.

We validated the prototypes with the categories out of which they were generated. This showed

	category 1	category 2	category 3	category 4	category 5	category 6	category 7	category 8	category 9	category 10	category 11	category 12	category 13	category 14	category 15	standalones
prototype 1	1.000	0.018	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.008	0.003	0.000	0.000	0.000
prototype 2	0.018	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
prototype 3	0.000	0.000	1.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
prototype 4	0.626	0.350	0.235	0.546	0.287	0.243	0.039	0.391	0.202	0.208	0.469	0.464	0.597	0.138	0.376	0.193
prototype 5	0.005	0.002	0.000	0.134	0.571	0.291	0.000	0.004	0.054	0.003	0.021	0.074	0.005	0.001	0.009	0.013
prototype 6	0.000	0.000	0.000	0.202	0.353	0.700	0.007	0.008	0.319	0.001	0.042	0.010	0.000	0.006	0.002	0.055
prototype 7	0.187	0.294	0.090	0.115	0.187	0.213	0.494	0.277	0.248	0.167	0.214	0.182	0.148	0.273	0.323	0.247
prototype 8	0.167	0.154	0.007	0.102	0.090	0.120	0.040	0.490	0.129	0.038	0.328	0.149	0.080	0.137	0.234	0.075
prototype 9	0.000	0.000	0.000	0.028	0.089	0.188	0.011	0.010	0.537	0.000	0.075	0.006	0.000	0.011	0.004	0.041
prototype 10	0.093	0.153	0.164	0.116	0.143	0.116	0.080	0.324	0.162	0.458	0.213	0.048	0.081	0.118	0.092	0.155
prototype 11	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.016	0.000	0.000	1.000	0.000	0.000	0.004	0.000	0.000
prototype 12	0.205	0.064	0.002	0.046	0.053	0.018	0.000	0.053	0.009	0.003	0.084	0.490	0.243	0.017	0.129	0.005
prototype 13	0.239	0.071	0.000	0.000	0.000	0.000	0.000	0.005	0.000	0.001	0.004	0.098	0.490	0.001	0.022	0.001
prototype 14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.004	0.000	0.000	1.000	0.000	0.000
prototype 15	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000

Table 3: Averages over the similarities of all categories to all prototypes
Intensity of color indicates higher values. Values have been rounded down to three decimal places.

that the abstraction step of using prototypes retains the information of the original categories while at the same time representing some flexibility that would be missing if we used fixed categories. It did not show how the prototypes generalize to other users or other settings. We had considered some kind of cross validation, using only a subset of our data to generate the prototypes. But since single users differ in their categorization, we would not have had any suitable measure of the validity of our results. A better test will be the use of the prototypes for automatically filling a kitchen and then asking users to find the objects.

Having a basis of human made prototypes, we will now be able to conduct further experiments like the one mentioned. We will be able to evaluate if our approach is reasonable to be one day implemented on a kitchen robot stowing kitchen objects in reasonable places or fetching similar items if a desired item is missing. In future experiments we are planning to find a better representation for the feature *material*. We are going to evaluate "subprototypes" representing different materials. We are also planning to compare our current results with those to be found by cluster algorithms, as well as an evaluation of our approach if it can be applied more widely, e.g. in order to identify similar songs, people in a social network or movies. Further, we are going to experimentally identify the critical features of kitchen objects by conducting a grouping experiment. Likewise, we are aware that the categories and prototypes we identified refer to a specific task. It is possible or even likely that people use different prototypes or feature weights for different tasks. We assumed that for the storage of objects geometric properties of the object are most important. When the task is to set a table, the intended purpose of the object and cultural conventions play a larger role and objects would be grouped differently.

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References

[1] Amélie Cordier, Valmi Dufour-Lussier, Jean Lieber, Emmanuel Nauer, Fadi Badra, Julien Cojan, Emmanuelle Gaillard, Laura Infante-Blanco, Pascal Molli, Amedeo Napoli, and Hala Skaf-Molli. Taaable: A case-based system for personalized cooking. In Stefania Montani and Lakhmi C. Jain,

editors, *Studies in Computational Intelligence - Successful Case-based Reasoning Applications-2*, volume 494, pages 121–162. Springer, 2014.

[2] Emmanuelle Gaillard, Laura Infante-Blanco, Jean Lieber, and Emmanuel Nauer. Tuuurbine: A Generic CBR Engine over RDFS. In Luc Lamontagne and Enric Plaza, editors, *Case-Based Reasoning Research and Development*, pages 140–154. Springer International Publishing, Cork, Ireland, 8765 edition, 2014.

[3] Emmanuelle Gaillard, Jean Lieber, and Emmanuel Nauer. Improving Case Retrieval Using Typicality. In E. Hüllermeier and M. Minor, editors, *Case-Based Reasoning Research and Development: 23rd International Conference, ICCBR*, pages 165–180, Frankfurt am Main, 2015. Springer International Publishing.

[4] Alexander Klippel, David M Mark, Jan Oliver Wallgrün, and David Stea. Conceptualizing Landscapes: A comparative study of landscape categories with Navajo and English-speaking participants. In S I Fabrikant, M Raubal, M Bertolotto, C Davies, S M Freundschuh, and S Bell, editors, *Spatial Information Theory: 12th International Conference, COSIT 2015, Santa Fe, NM, USA, October 12-16, 2015, Proceedings*, pages 268–288. Berlin: Springer, Santa Fe, NM, USA, 2015.

[5] Alexander Klippel, Chris Weaver, and Anthony C. Robinson. Analyzing Cognitive Conceptualizations Using Interactive Visual Environments. *Cartography and Geographic Information Science*, 38(1):52–68, 2011.

[6] Séverin Lemaignan. *Grounding the Interaction: Knowledge Management for Interactive Robots.* PhD thesis, 2012.

[7] Antonio Lieto. A computational framework for concept representation in cognitive systems and architectures: Concepts as heterogeneous proxytypes. *Procedia Computer Science*, 41:6–14, 2014.

[8] Antonio Lieto, Daniele P. Radicioni, and Valentina Rho. Dual PECCS: A Cognitive System for Conceptual Representation and Categorization. *Journal of Experimental & Theoretical Artificial Intelligence*, 29(2):433–452, mar 2017.

[9] Edouard Machery. *Doing without concepts.* Oxford University Press, Oxford [i.a.], 2009.

[10] Douglas L. Medin and Marguerite M. Schaffer. Context theory of classification learning. *Psychological Review*, 85(3):207–238, 1978.

[11] John Paul Minda and J. David Smith. Prototype models of categorization: basic formulation, predictions, and limitations. In Emmanuel M. Pothos, editor, *Formal approaches in categorization*, pages 40–64. Cambridge Univ. Press, Cambridge, 1st edition, 2011.

[12] Ana Maria Olteţeanu and Zoe Falomir. Object replacement and object composition in a creative cognitive system. Towards a computational solver of the Alternative Uses Test. *Cognitive Systems Research*, 39:15–32, 2016.

[13] Jesse J. Prinz. *Furnishing the Mind: Concepts and Their Perceptual Basis.* MIT Press, Cambridge, Massachusetts, 1st edition, 2002.

[14] Eleanor Rosch. Cognitive representations of semantic categories. *Journal of Experimental Psychology: General*, 104(3):192–233, 1975.

[15] David J. Smith and John Paul Minda. Thirty categorization results in search of a model. *Experimental Psychology: Learning, Memory, and Cognition*, 26(1):3–27, 2000.

[16] Moritz Tenorth. *Knowledge Processing for Autonomous Robots.* PhD thesis, 2011.

[17] Alisa Volkert and Alexandra Kirsch. Prototype-based Knowledge Representation for an Improved Human-robot Interaction. *4. Interdisziplinärer Workshop Kognitive Systeme 2015-Proceedings*, 3(2):213, 2015.

[18] Manfred Wolff, Peter Hauck, and Wolfgang Küchlin. *Mathematik für Informatik und Bioinformatik.* Springer-Verlag Berlin Heidelberg, 2004.