Construal Level Theory as a Means for Anticipating Human-Robot Interactions

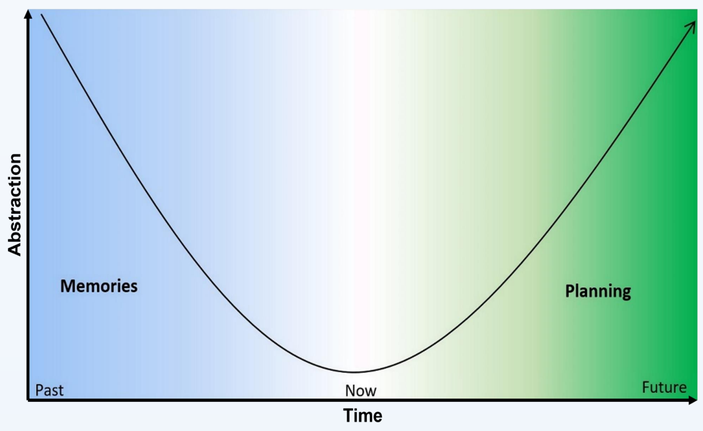
Alan R. Wagner, Sarah Rajtmajer, and Christopher McClurg

ABSTRACT

This work describes our effort to develop methods for human-robot interaction based on Construal Level Theory (CLT). CLT is a process which connects abstraction to physical and temporal distance. With respect to interactions with people, CLT may govern how to interact with different categories of people. We present preliminary results showing that we can create superordinate, high-level construals. Upcoming efforts will demonstrate the use of this approach by a robot to plan for interactions with people.

WHAT IS CONSTRUAL LEVEL THEORY?

- Construal Level Theory (CLT) hypothesizes a process by which an individual uses prototypical experiences from memory to generate a rough estimate of some future situation [1]–[3]. .
- Specifically, the theory states that people create mental abstractions in order to predict outcomes, form counterfactauals, and guide behavior with respect to distal times, places, and actions.
- As a person's psychological distance (subjective experience that something is close or far away) to a future event decreases, the prototypical experience moves from rough estimate to actionable plan by decorating the mental construct with additional information.

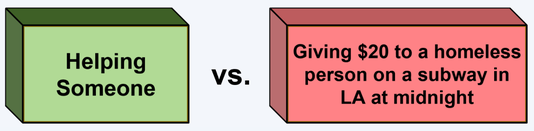


- The construal process offers a flexible method for planning, enabling a person to hold off adding details to their evolving plan until those details are needed, yet also affording opportunities for contingency planning.
- Researchers from the planning and RL communities have studied abstraction as part of the planning and policy generation process [4]. CLT goes beyond these efforts by connecting the construal process not only to planning and action selection, but also to a person's perception and evaluation of objects, events, and other people [2], [5], [6].

WHY CONSTRUAL LEVEL THEORY?

- CLT describes a process for abstracting away the details surrounding a robot's experience as psychological distance increases. Abstract experiences may serve as initial solutions to new problems, and may be used to limit the space of its search for solutions.
- CLT defines a construal process that may enable a robot to manage competing goals at the same time by utilizing temporal or physical distance as a moderator of those goals.
- CLT may lend insight into the reward/ utility shaping process itself [3], [12]. CLT does not define what, how or when rewards are obtained; however, CLT proposes certain actions will be seen as more positive in the distant future than in the near term. These actions will be represented as high level construals and the attributes of these will be positive overall [1].

Example of reward shaping



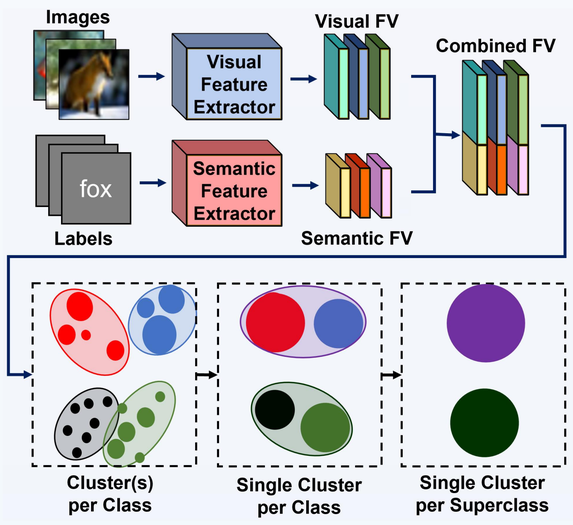
- CLT is supported by a great deal of psychological evidence, e.g., visual perception, categorization, and action identification [3], [7]–[9].

RELATED WORK

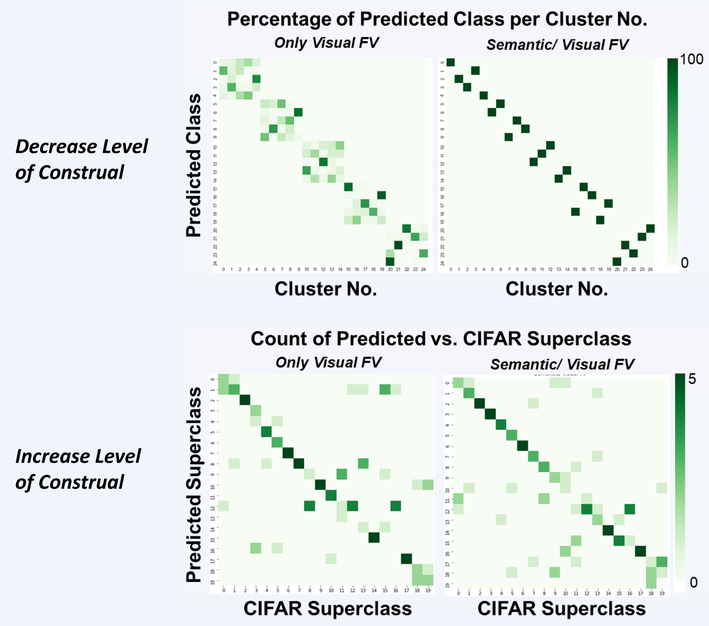
- ***Hierarchical planning*** requires elements of search and task decomposition. From the planning perceptive, our research ties task decomposition to psychological distance, using distance as a reactive, environmental cue to decompose tasks (create low-level construals) that are immediately relevant.
- ***Reinforcement Learning*** has limitations: need for large data sets, lack of ability to transfer tasks learned in one context to another, and difficulty of designing/ learning reward functions [20]. Our research will use CLT to represent knowledge about items, events, and people to guide behavior.
- ***Interpersonal interaction*** studies how people plan conversations and generate expectations about future interactions. CLT posits that as the time for an interpersonal interaction draws near, each person will develop increasingly specific plans meant to shape the interaction [3], [22]. Categorical or stereotyped models play an important role in deciding who, how, and when to cooperate with others.

INITIAL WORK

- We are currently adapting a continual learning algorithm, Centroid-Based Concept Learning (CBCL), to create clusters representing different levels of construal.
- CBCL generates a set of concepts in the form of centroids for each class using a cognitively-inspired clustering approach (denoted as Agg-Var clustering).
- A schematic for the adapted clustering process is as shown. Note that the visual feature extractor is a Resnet-34 model with ImageNet weights, while the semantic feature extractor uses ConceptNet.



- Higher-level concepts can be generated by merging subordinate clusters with k-means clustering. Lower-level concepts can be generated by splitting superordinate clusters with k-means clustering.
- Initially, we focused on objects in the CIFAR-100 dataset. This dataset includes images with a unique 100 class and 20 superclass labels.
- The creation of construals was tested, comparing the ability to discriminate between classes (to decrease level of construal) or merge similar to CIFAR (to increase level of construal).



ACKNOWLEDGEMENTS

This work was supported by Air Force Office of Scientific Research (AFOSR) grant number FA9550-21-1-0197.

CONCLUSIONS

Although still in the early phases, we hope to use CLT to allow robots to anticipate and predict how to interact with unknown people in new situations. CLT describes a process tying abstraction to distance in the future. We believe that this process can be used to categorize interactions in terms of the participants and with respect to the context. We hope to ultimately connect this process with reinforcement learning and game theory to develop robots capable of interacting with a wide variety of people in a wide variety of situations.

REFERENCES

[1] Y. Trope and N. Liberman, "Temporal construal." Psychological review, vol. 110, no. 3, p. 403, 2003.

[2] Y. Trope, N. Liberman, and C. Wakslak, "Construal levels and psychological distance: Effects on representation, prediction, evaluation, and behavior," Journal of consumer psychology, vol. 17, no. 2, pp. 83–95, 2007.

[3] Y. Trope and N. Liberman, "Construal-level theory of psychological distance." Psychological review, vol. 117, no. 2, p. 440, 2010.

[4] M. B. Chang, A. Gupta, S. Levine, and T. L. Griffiths, "Automatically composing representation transformations as a means for generalization," 2019.

[5] K. Fujita, M. D. Henderson, J. Eng, Y. Trope, and N. Liberman, "Spatial distance and mental construal of social events," Psychological Science, vol. 17, no. 4, pp. 278–282, 2006.

[6] C. J. Wakslak, S. Nussbaum, N. Liberman, and Y. Trope, "Representations of the self in the near and distant future." Journal of personality and social psychology, vol. 95, no. 4, p. 757, 2008.

[7] B. S. Moore, D. R. Sherrod, T. J. Liu, and B. Underwood, "The dispositional shift in attribution over time," Journal of Experimental Social Psychology, vol. 15, no. 6, pp. 553–569, 1979.

[8] N. Liberman and Y. Trope, "The role of feasibility and desirability considerations in near and distant future decisions: A test of temporal construal theory." Journal of personality and social psychology, vol. 75, no. 1, p. 5, 1998.

[9] N. Liberman, M. D. Sagristano, and Y. Trope, "The effect of temporal distance on level of mental construal," Journal of experimental social psychology, vol. 38, no. 6, pp. 523–534, 2002.

[10] J. R. Busemeyer and A. Diederich, Cognitive modeling. Sage, 2010.

[11] J. C. Turner, M. A. Hogg, P. J. Oakes, S. D. Reicher, and M. S. Wetherell, Rediscovering the social group: A self-categorization theory. Basil Blackwell, 1987.

[12] A. Fishbach and T. Eyal, "The motivation-emotion matching hypothesis," ACR North American Advances, 2010.

[13] K. Christoff, K. Keramatian, A. M. Gordon, R. Smith, and B. Madler, "Prefrontal organization of cognitive control according to levels of abstraction," Brain research, vol. 1286, pp. 94–105, 2009.

[14] J. J. Ribas-Fernandes, A. Solway, C. Diuk, J. T. McGuire, A.G. Barto, Y. Niv, and M. M. Botvinick, "A neural signature of hierarchical reinforcement learning," Neuron, vol. 71, no. 2, pp. 370–379, 2011.

[15] E. D. Sacerdoti, "Planning in a hierarchy of abstraction spaces," Artificial intelligence, vol. 5, no. 2, pp. 115–135, 1974

[16] D. E. Wilkins, "Domain-independent planning representation and plan generation," Artificial Intelligence, vol. 22, no. 3, pp. 269–301, 1984.

[17] N. D. Daw and D. Shohamy, "The cognitive neuroscience of motivation and learning," Social Cognition, vol. 26, no. 5, pp. 593–620, 2008.

[18] N. D. Daw, S. J. Gershman, B. Seymour, P. Dayan, and R. J. Dolan, "Model-based influences on humans' choices and striatal prediction errors," Neuron, vol. 69, no. 6, pp. 1204–1215, 2011.

[19] K. Arulkumaran, M. P. Deisenroth, M. Brundage, and A. A. Bharath, "Deep reinforcement learning: A brief survey," IEEE Signal Processing Magazine, vol. 34, no. 6, pp. 26–38, 2017.

[20] A. Irpan, "Deep reinforcement learning doesn't work yet," https://www.alexirpan.com/2018/02/14/rl-hard.html, 2018.

[21] J. Fu, K. Luo, and S. Levine, "Learning robust rewards with adversarial inverse reinforcement learning," arXiv preprint arXiv:1710.11248, 2017.

[22] D. T. Gilbert, "Ordinary personology," The handbook of social psychology, vol. 2, pp. 89–150, 1998.

[23] D. J. Schneider, The psychology of stereotyping. Guilford Press, 2005.

[24] C. N. Macrae and G. V. Bodenhausen, "Social cognition: Thinking categorically about others," Annual review of psychology, vol. 51, no. 1, pp. 93–120, 2000.

[25] A. Ayub and A. R. Wagner, "CBCL: Brain inspired model for RGB-D indoor scene classification," arXiv preprint arXiv:1911.00155, vol. 2, no. 3, 2019.

[26] A. Ayub and A. R. Wagner, "Cognitively-inspired model for incremental learning using a few examples," in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops, 2020, pp. 222–223.

[27] M. L. Mack, B. C. Love, and A. R. Preston, "Building concepts one episode at a time: The hippocampus and concept formation," Neuroscience Letters, vol. 680, pp. 31–38, 2018.

[28] A. R. Wagner, "Robots that stereotype: creating and using categories of people for human-robot interaction," Journal of Human-Robot Interaction, vol. 4, no. 2, pp. 97–124, 2015.

[29] A. R. Wagner, "Using cluster-based stereotyping to foster human-robot cooperation," in 2012 IEEE/RSJ International Conference on Intelligent Robots and Systems. IEEE, 2012, pp. 1615–1622.