In-Context Analogical Reasoning with Pre-Trained Language Models

Xiaoyang Hu, Shane Storks, Richard Lewis, & Joyce Chai   University of Michigan

Introduction

Analogical reasoning enables humans to understand novel problems by connecting to past experience [1]. While we make analogies without direct training, conventional AI systems require thousands of training examples to perform well on benchmark tasks [2].

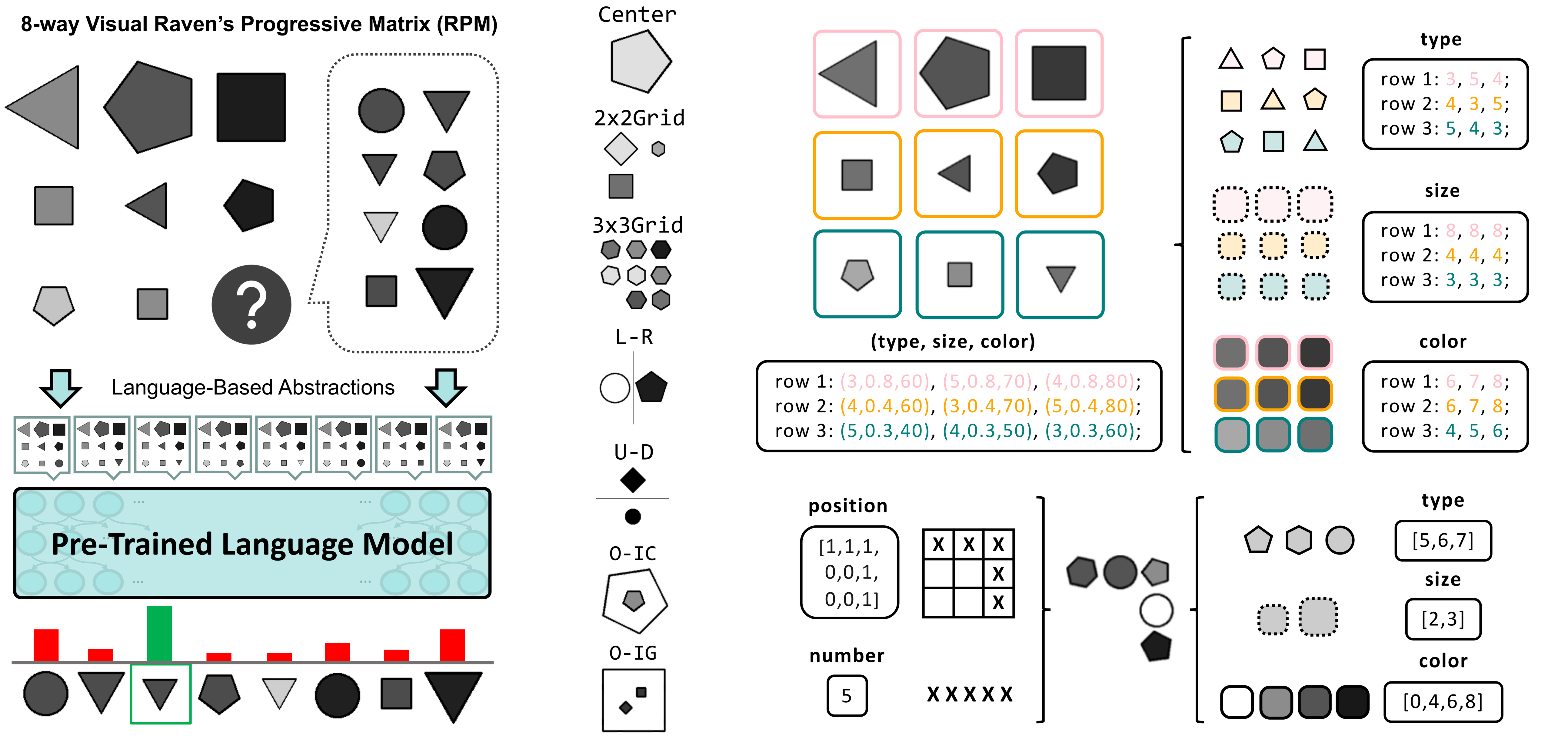
Cognitive science has identified connections between language and analogy-making in humans:

- Numbers in language enable numerical analogies [3]
- Spatial relations in language enable spatial analogies [4]
- Assigning nonsense names to abstract relations enhances analogy-making with them [5]

Inspired by this, **we explore the application of pre-trained language models (PLMs) to analogy-making.**

Problem Definition & Applied Abstractions

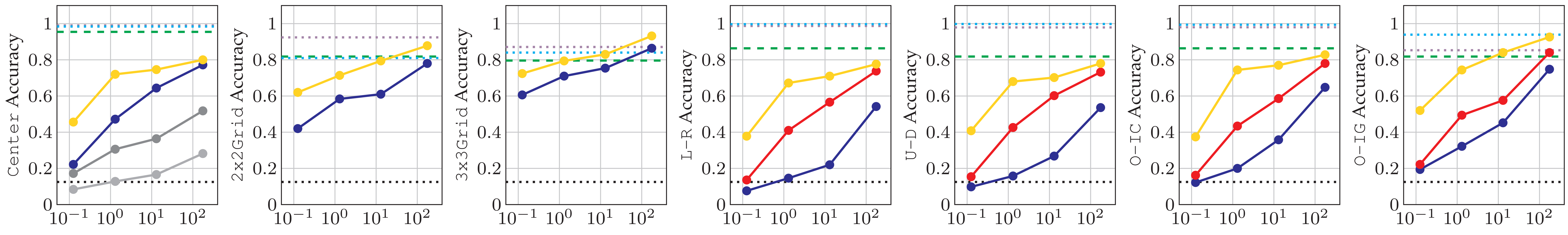
We apply PLMs to Raven's Progressive Matrices (RPM) [6] by converting the RAVEN dataset into text prompts [7].



Impact of Abstractions

On RAVEN dataset [7], **PLMs achieve striking zero-shot performance increasing with model complexity,** approaching humans and supervised models.

Human · Rel-AIR [8] · CoPINet + ACL [9] · Random · Attr. Naming · Comp. Decomp. · Comp. & Attr. Decomp.



Model Size (Billion Parameters)

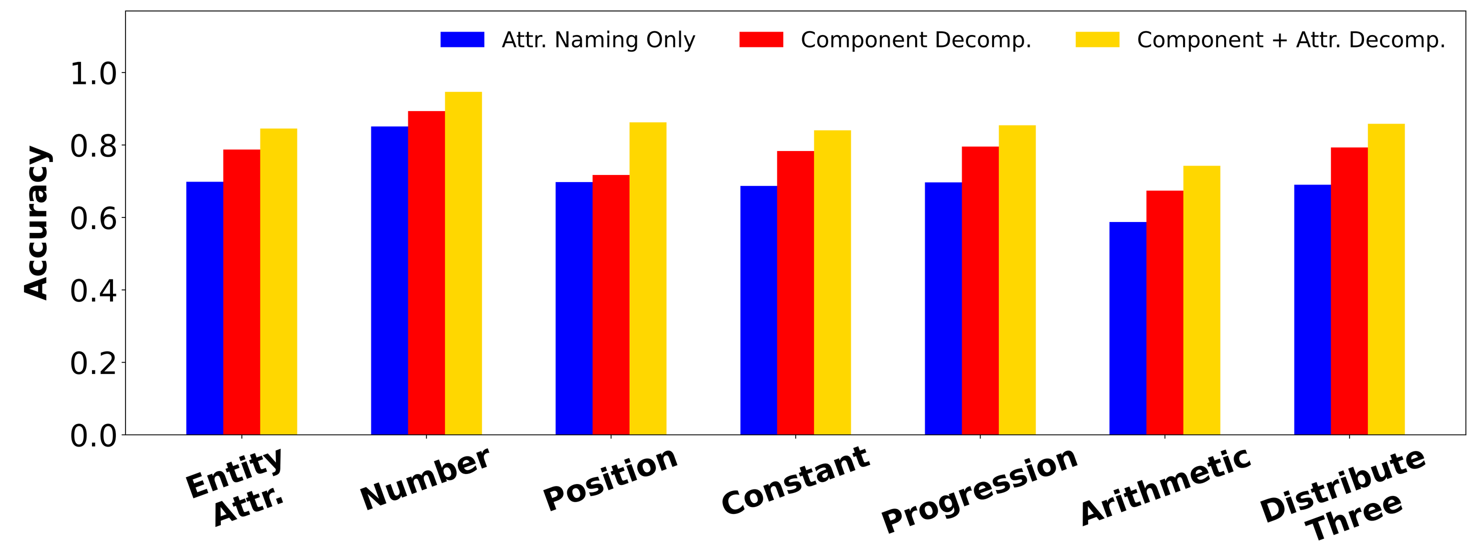
Analysis on Distracting Attributes

PLMs show robustness to distracting features injected into prompts.

Distractor Values	Naming Abstractions	Naming & Decomposition
RAVEN	76.0% (-1.2%)	80.0% (-0.0%)
Random	72.6% (-4.6%)	77.8% (-2.2%)

The capability to distinguish important features from background features is essential to analogy-making. Future work should explore this further.

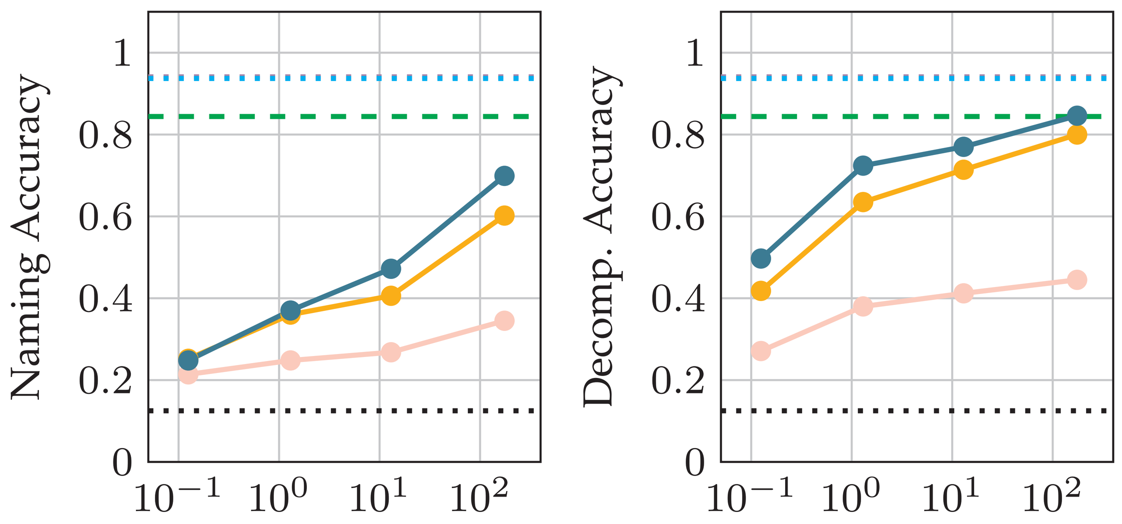
Analysis on Attributes & Relations



Analysis on In-Context Learning

Most of PLM performance comes from in-context learning, but, surprisingly, some comes from prior knowledge.

Human · Rel-AIR [8] · CoPINet + ACL [9] · Random · 1 Row · 2 Rows · 3 Rows



Sub-Task	1 Row	2 Rows	3 Rows	Human
Center	36.8%	69.2%	77.2%	95.6%
2x2Grid	54.0%	71.0%	78.0%	81.8%
3x3Grid	**73.0%**	**85.2%**	**86.4%**	79.6%
L-R	14.0%	38.2%	54.2%	86.4%
U-D	12.4%	42.0%	53.6%	81.8%
O-IC	19.6%	53.6%	64.8%	86.4%
O-IG	32.0%	62.2%	74.8%	81.8%

Links

Pre-Print   Code

References

[1] K.J. Holyoak. Analogical thinking and human intelligence. *Advances in the Psychology of Human Intelligence*, 2, 1984.

[2] M. Mitchell. Abstraction and analogy-making in artificial intelligence. *Annals of the New York Academy of Sciences*, 1505(1), 2021.

[3] P. Gordon. Numerical cognition without words: Evidence from Amazonia. *Science*, 306(5695), 2004.

[4] D. Gentner, A. Özyürek, Ö. Gürcanli, and S. Goldin-Meadow. Spatial language facilitates spatial cognition: Evidence from children who lack language input. *Cognition*, 127(3), 2013.

[5] S. Christie and D. Gentner. Language helps children succeed on a classic analogy task. *Cognitive Science*, 38(2), 2014.

[6] J.C. Raven and J.H. Court. *Raven's progressive matrices.* Western Psychological Services Los Angeles, 1938.

[7] C. Zhang, F. Gao, B. Jia, Y. Zhu, and S.-C. Zhu. RAVEN: A dataset for relational and analogical visual reasoning. In *CVPR*, 2019.

[8] S. Spratley, K. Ehinger, and T. Miller. A closer look at generalisation in RAVEN. In *ECCV*, 2020.

[9] Y. Kim, J. Shin, E. Yang, and S.J. Hwang. Few-shot visual reasoning with meta-analogical contrastive learning. In *NeurIPS*, 2020.