

Towards Learning to Reason: Comparing LLMs with Neuro-Symbolic on Arithmetic Relations in Abstract Reasoning

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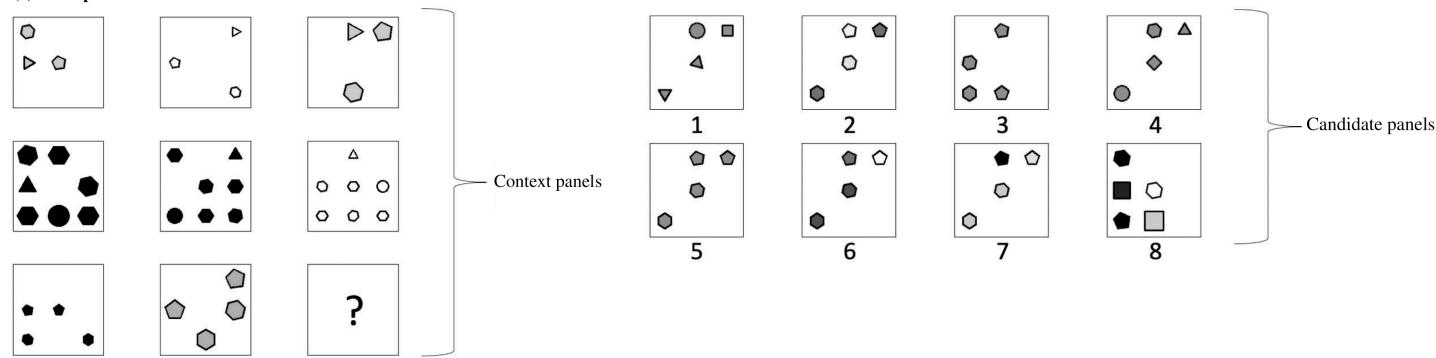
The authors are

- **Michael Hersche**(ML, Hyperdimensional Computing, Vector-symbolic Architectures),
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- Roger Wattenhofer(Distributed computing, algorithms),
- Abu Sebastian(In-memory computing, Brain-inspired computing),
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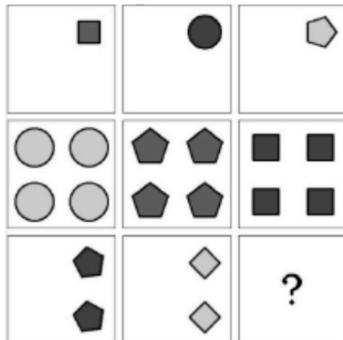
who mainly focus on machine learning and symbolic reasoning.

RPM: Task Introduction

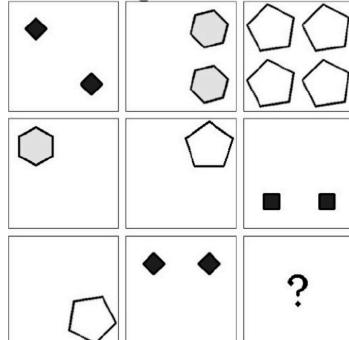
Raven's Progressive Matrices



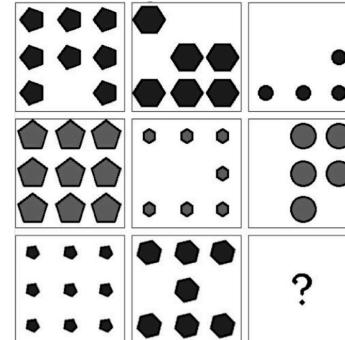
Position: Constant



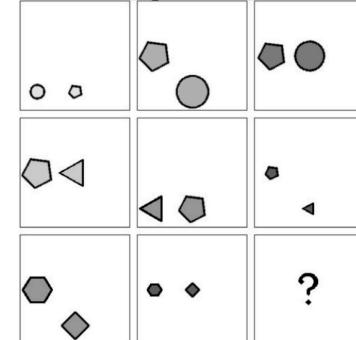
Number: Arithmetic plus



Number: Progression (-2)



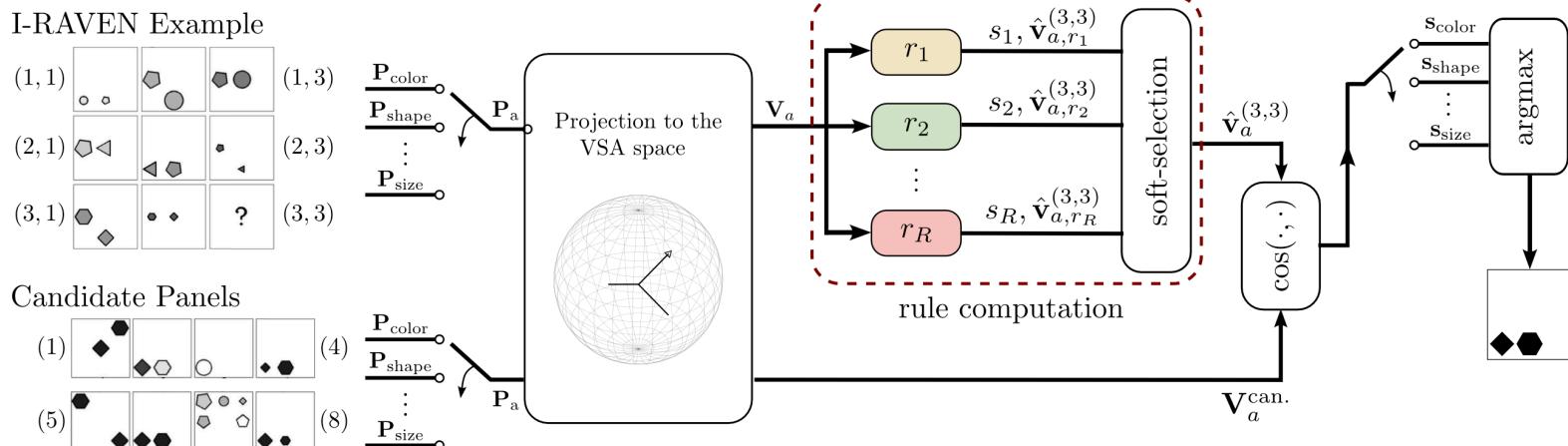
Position: Distribute three



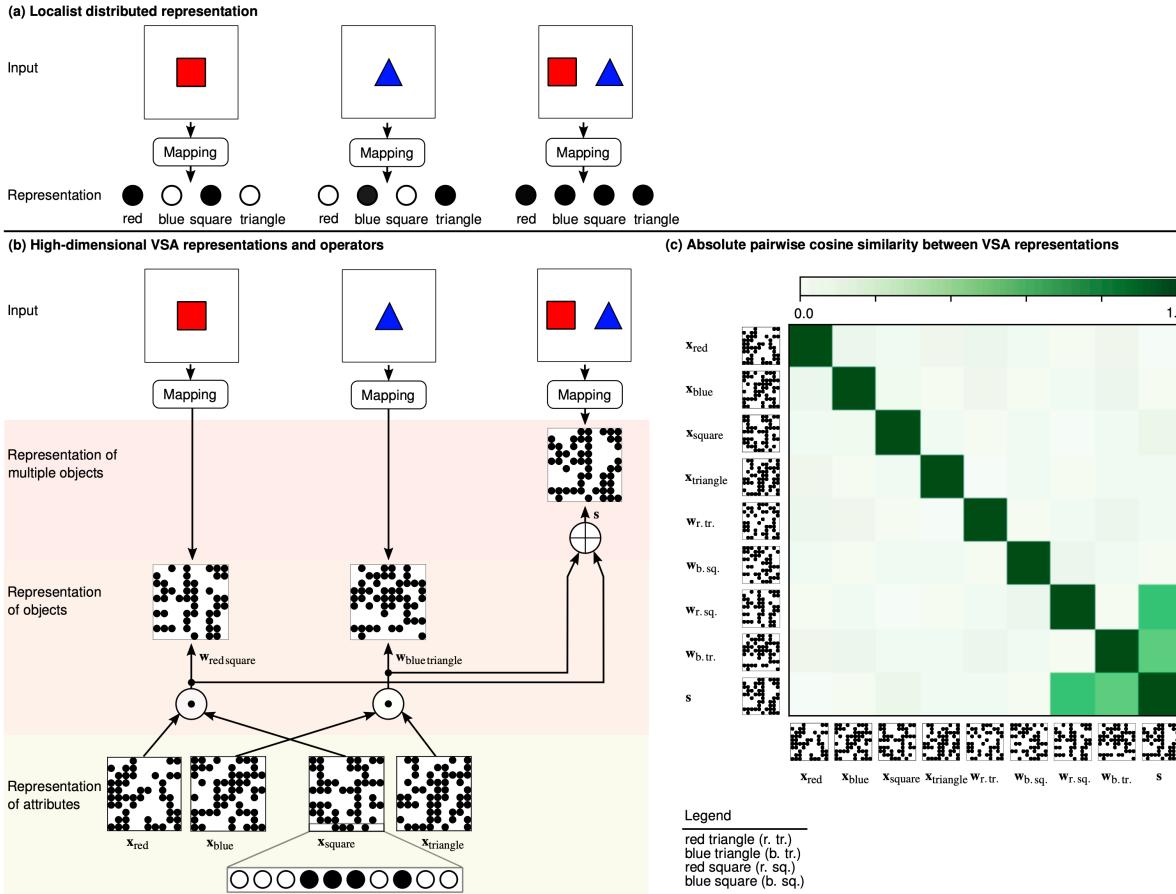
ARLC: An Overview

Abductive Rule Learner with Context-awareness

Panel → Probability Mass Function(PMF) → Vector-Symbolic Architectures(VSA)
→ Rule Computation → Soft Selection



Vector-Symbolic Architectures(VSA): Intuition



Perception: Panel \rightarrow PMF \rightarrow VSA

- For every attribute a , each panel's label is translated to a probability mass function (PMF) $\mathbf{p}_a^{(i,j)}$, (i, j) is the coordinate of the panel.
- The PMF is projected into the VSA space as

$$\mathbf{v}_a^{(i,j)} = \sum_{k=1}^N \mathbf{p}_a^{(i,j)}[k] \cdot \mathbf{b}[k]$$

\mathbf{b} is a *Dictionary* in the form of binary generalized sparse block codes, specifically, a 1024 dimensional vector divided into 4 blocks of equal length, where only one randomly selected element per block is set to 1.

N is number of possible values that the attribute a can take.

Operation	Binary GSBCs	Equivalent in \mathbb{R}
Binding (\otimes)	Block-wise circular convolution (\circledast)	Addition +
Unbinding (\oslash)	Block-wise circular correlation (\odot)	Subtraction -
Bundling (\oplus)	Sum & normalization	—
Similarity (\odot)	Cosine similarity ($\cos(\cdot, \cdot)$)	—

Learning Context-Augmented RPM Rules

Rules can be generalized

Rule	VSA formulation	
Constant	$\hat{\mathbf{a}}^{(3,3)} = \mathbf{a}^{(3,2)} = \mathbf{a}^{(3,1)}$	
Arithmetic plus	$\hat{\mathbf{a}}^{(3,3)} = \mathbf{a}^{(3,1)} \circledast \mathbf{a}^{(3,2)}$	$\rightarrow \hat{\mathbf{a}}^{(3,3)} = (\mathbf{c}_1 \circledast \mathbf{c}_2 \circledast \mathbf{c}_3) \otimes (\mathbf{c}_4 \circledast \mathbf{c}_5 \circledast \mathbf{c}_6)$
Progression positive	$\hat{\mathbf{a}}^{(3,3)} = \mathbf{a}^{(3,2)} \circledast (\mathbf{a}^{(3,2)} \otimes \mathbf{a}^{(3,1)})$	
Distribute three	$\hat{\mathbf{a}}^{(3,3)} = (\mathbf{a}^{(1,1)} \circledast \mathbf{a}^{(1,2)} \circledast \mathbf{a}^{(1,3)}) \otimes (\mathbf{a}^{(3,1)} \circledast \mathbf{a}^{(3,2)})$	

$$r = (\mathbf{c}_1 \circledast \mathbf{c}_2 \circledast \mathbf{c}_3 \circledast \mathbf{c}_4 \circledast \mathbf{c}_5 \circledast \mathbf{c}_6) \otimes (\mathbf{c}_7 \circledast \mathbf{c}_8 \circledast \mathbf{c}_9 \circledast \mathbf{c}_{10} \circledast \mathbf{c}_{11} \circledast \mathbf{c}_{12})$$

$$\mathbf{c}_k = \sum_{i=1}^I w_k^i \cdot \mathbf{x}_i + \sum_{j=1}^J u_k^j \cdot \mathbf{o}_j + v_k \cdot \mathbf{e}$$

$$\text{s.t. } \sum_{i=1}^I w_k^i + \sum_{j=1}^J u_k^j + v_k = 1; w_k^i, u_k^j, v_k \geq 0$$

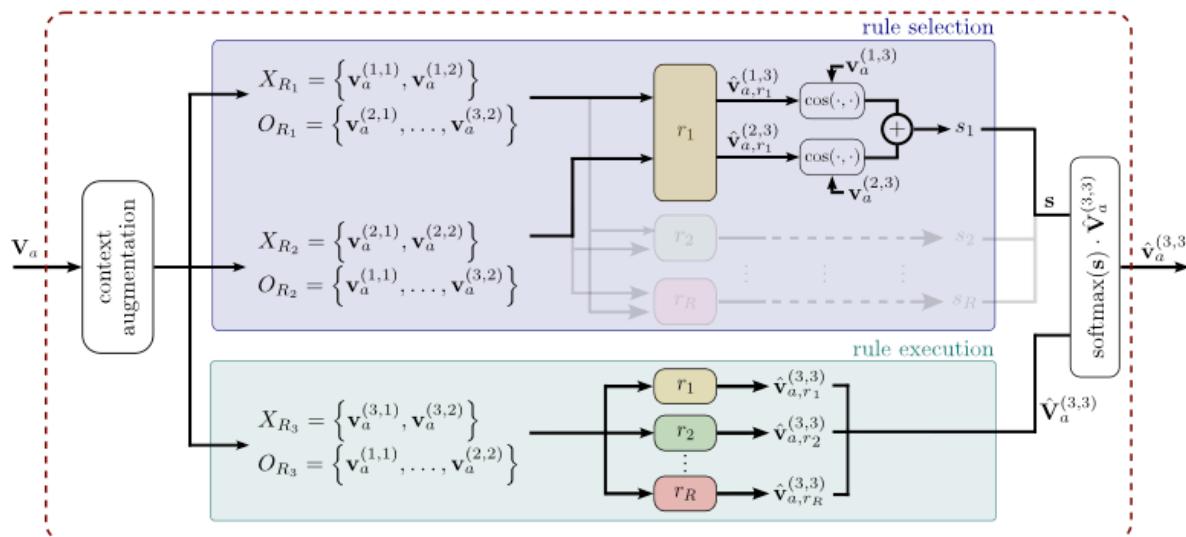
Training & Reasoning(Inference)

Learning & Executing of the Rules

$$\text{Rule confidence: } s_r = \sum_{i=1}^3 \cos(\mathbf{v}_a^{(i,3)}, \hat{\mathbf{v}}_{a,r}^{(i,3)})$$

Softmax based on rule confidence is in use to enable *soft selection* of the final VSA.

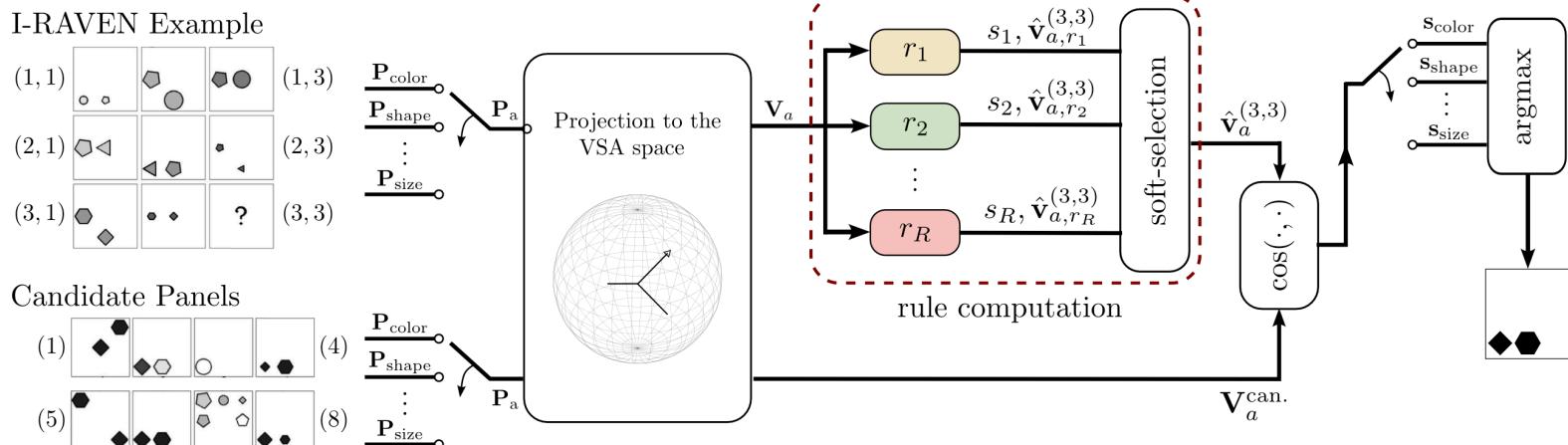
$$\text{Training Loss: } \mathcal{L} = 1 - \sum_{i=1}^3 \cos(\mathbf{v}_a^{(i,3)}, \hat{\mathbf{v}}_a^{(i,3)})$$



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LLM-based RPM solving & Results

prompts used for different datasets

a) LLM prompts for I-RAVEN

System: Complete the Raven's progressive matrix:
User: Only return the missing numbers!
row 1: 5, 5, 5;
row 2: 3, 3, 3;
row 3: 6, 6,
Output: 6

Attribute: **shape**
Rule: **constant**
Correct answer: 6

System: Complete the Raven's progressive matrix:
User: Only return the missing numbers!
row 1: 6, 6, 6;
row 2: 4, 4, 4;
row 3: 2, 2,
Output: 2

Attribute: **size**
Rule: **constant**
Correct answer: 2

System: Complete the Raven's progressive matrix:
User: Only return the missing numbers!
row 1: 8, 2, 6;
row 2: 1, 0, 1;
row 3: 8, 7,
Output: 6

Attribute: **color**
Rule: **arithmetic -**
Correct answer: 1

b) LLM prompts for our new I-RAVEN-X

System: Complete the Raven's progressive matrix:
User: Only return the missing numbers!
row 1: 320, 322, 324, 326, 328, 330, 332, 334, 336, 338;
row 2: 718, 720, 722, 724, 726, 728, 730, 732, 734, 736;
row 3: 224, 226, 228, 230, 232, 234, 236, 238, 240,
Output: 242

Attribute: **shape**
Rule: **progression**
Correct answer: 242

System: Complete the Raven's progressive matrix:
User: Only return the missing numbers!
row 1: 73, 73, 73, 73, 73, 73, 73, 73, 73;
row 2: 677, 677, 677, 677, 677, 677, 677, 677, 677;
row 3: 695, 695, 695, 695, 695, 695, 695, 695, 695,
Output: 695

Attribute: **size**
Rule: **constant**
Correct answer: 695

System: Complete the Raven's progressive matrix:
User: Only return the missing numbers!
row 1: 769, 667, 0, 4, 2, 20, 63, 3, 5, 5;
row 2: 848, 0, 0, 0, 387, 2, 106, 7, 308, 38;
row 3: 611, 2, 0, 0, 0, 0, 0, 551, 0,
Output: 352

Attribute: **color**
Rule: **arithmetic -**
Correct answer: 58

Method	Parameters	Accuracy
MLP [8]	300 k	97.6
SCL [5]	961 k	99.9 ^{±0.0}
PrAE [6]	n.a.	83.8 ^{±3.4}
NVSA [7]	n.a.	99.8 ^{±0.2}
Learn-VRF [8]	20 k	97.7 ^{±4.1}
GPT-3 [14]	175 b	86.4
Llama-3	70 b	85.0
GPT-4	unk.	93.2
ARLC _{progr}	n.a.	97.2 ^{±0.0}
ARLC _{p→l}	480	97.6 ^{±0.0}
ARLC _{learn}	480	98.4 ^{±1.5}

Discussion

A novel symbolic representation ~~at least to me~~

works both semantically and for rules

Introducing Differentiability

Possible Drawbacks

Might fail on non-toy tasks

The nature of this task demands minimal "reasoning", and I doubt its application in more complex tasks due to the **limited expressiveness** of arithmetic operations.

Not very explicit with the symbolic expression

Only center constellation?

Thank you for your attention

References to be updated.

Questions are welcome.

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