Demystifying Neuro-Symbolic AI for Software-Hardware Co-Design

Zishen Wan

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Advisors: Prof. Arijit Raychowdhury, Prof. Tushar Krishna



MLBench Workshop @ ASPLOS, March 30, 2025

Executive Summary

- **Understand** neuro-symbolic workloads from architecture and system perspective.
- Identify **optimization opportunities** for neuro-symbolic systems.
- Demonstrate orders of scalability and efficiency improvement of neuro-symbolic workload via **co-designed** system.

Neural Networks in Our Daily Life

Image Recognition

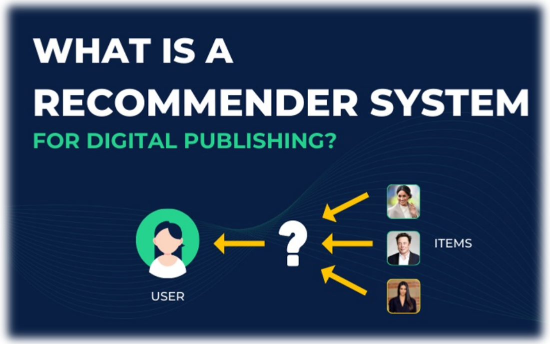
Speech Recognition

Language Translation

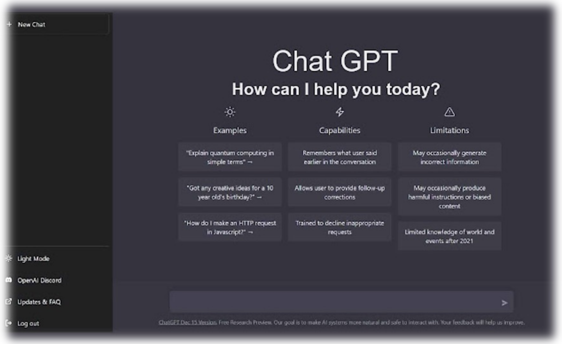
Autonomous Vehicle

Medical Diagnosis

Financial Services

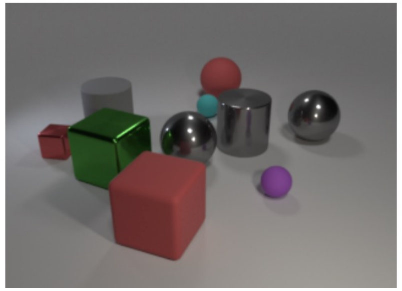


Recommendation Systems



ChatGPT

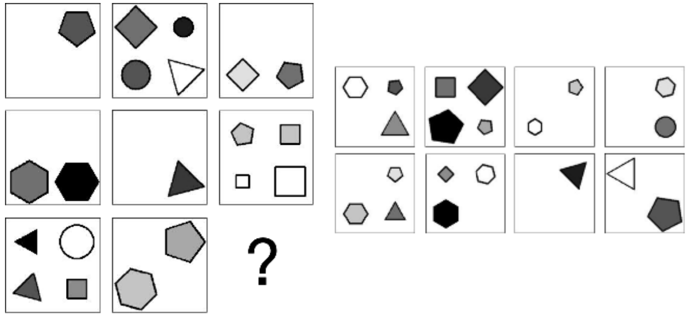
But... Is That Enough?



(i) *Remove all gray spheres. How many spheres are there?* (3), (ii) *Take away 3 cubes. How many objects are there?* (7), (iii) *How many blocks must be removed to get 1 block?* (2)

Complex Question Answering

NN accuracy: 50%

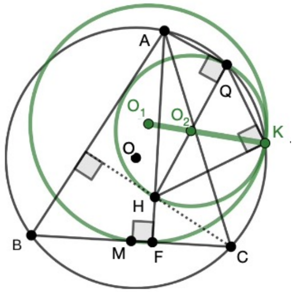


Abstract Reasoning

NN accuracy: 53%

IMO 2015 P3

"Let ABC be an acute triangle. Let (O) be its circumcircle, H its orthocenter, and F the foot of the altitude from A. Let M be the midpoint of BC. Let Q be the point on (O) such that QH ⊥ QA and let K be the point on (O) such that KH ⊥ KQ. Prove that the circumcircles (O_1) and (O_2) of triangles FKM and KQH are tangent to each other."



Automated Theorem Proving

NN accuracy: 20%

Interactive Learning

Scenario

Imagine that a stranger will give Hank one thousand dollars to break all the windows in his neighbor's house without his neighbor's permission. Hank carries out the stranger's request.

Imagine that there are five people who are waiting in line to use a single-occupancy bathroom at a concert venue. Someone at the back of the line needs to throw up immediately. That person skips to the front of the line instead of waiting in the back.

At a summer camp, there is a pool. Right next to the pool is a tent where the kids at the camp have art class. The camp made a rule that there would be no cannonballing in the pool so that the art wouldn't get ruined by the splashing water. Today, there is a bee attacking this kid, and she needs to jump into the water quickly. This kid cannonballs into the pool.

Ethical Decision Making

NN accuracy: 65%

Farmer John has N cows ($2 \leq N \leq 10^5$). Each cow has a breed that is either Guernsey or Holstein. As is often the case, the cows are standing in a line, numbered $1 \cdots N$ in this order.

Over the course of the day, each cow writes down a list of cows. Specifically, cow i's list contains the range of cows starting with herself (cow i) up to and including cow E_i ($i \leq E_i \leq N$).

FJ has recently discovered that each breed of cow has exactly one distinct leader. FJ does not know who the leaders are, but he knows that each leader must have a list that includes all the cows of their breed, or the other breed's leader (or both).

Help FJ count the number of pairs of cows that could be leaders. It is guaranteed that there is at least one possible pair.

Problem

Competitive Programming

NN accuracy: 8.7%

Interactive Learning: NN accuracy: 71%

But... Is That Enough?

(i) *Remove all gray spheres. How many spheres are there?* (3), (ii) *Take away 3 cubes. How many objects are there?* (7), (iii) *How many blocks must be removed to get 1 block?* (2)

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Neuro-Symbolic AI

Interactive Learning

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Problem

Competitive Programming

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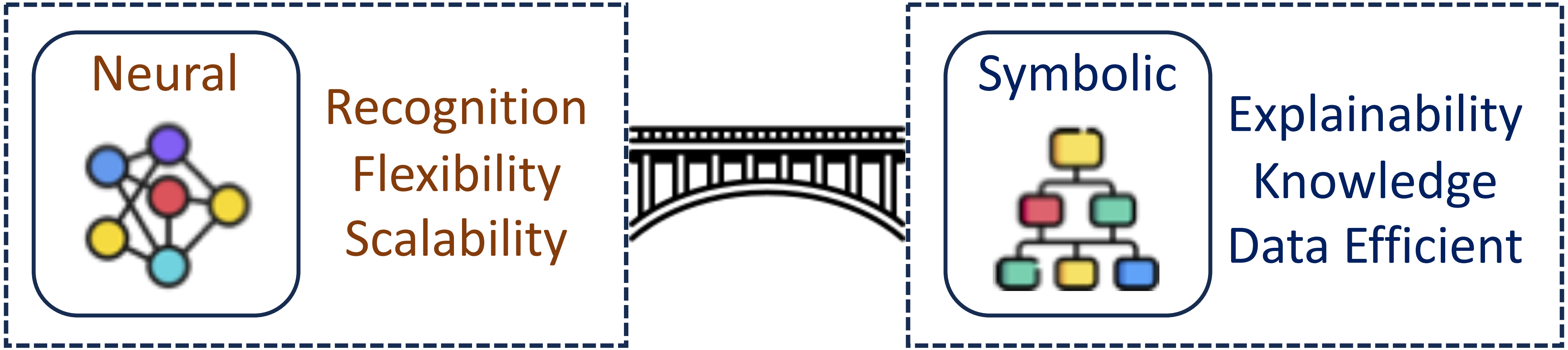
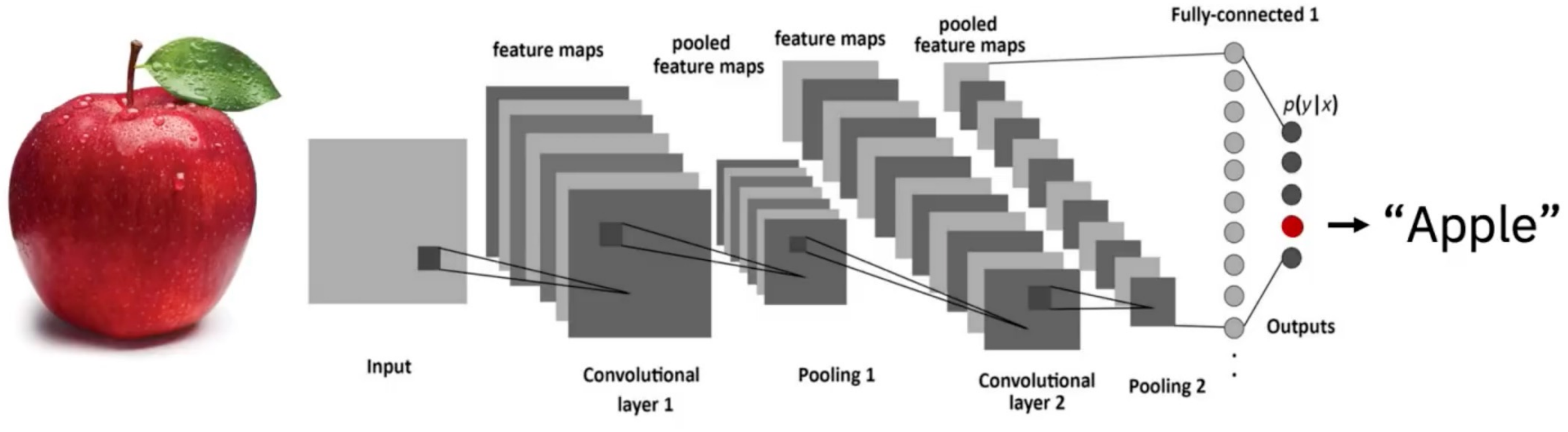
What is Neuro-Symbolic AI?



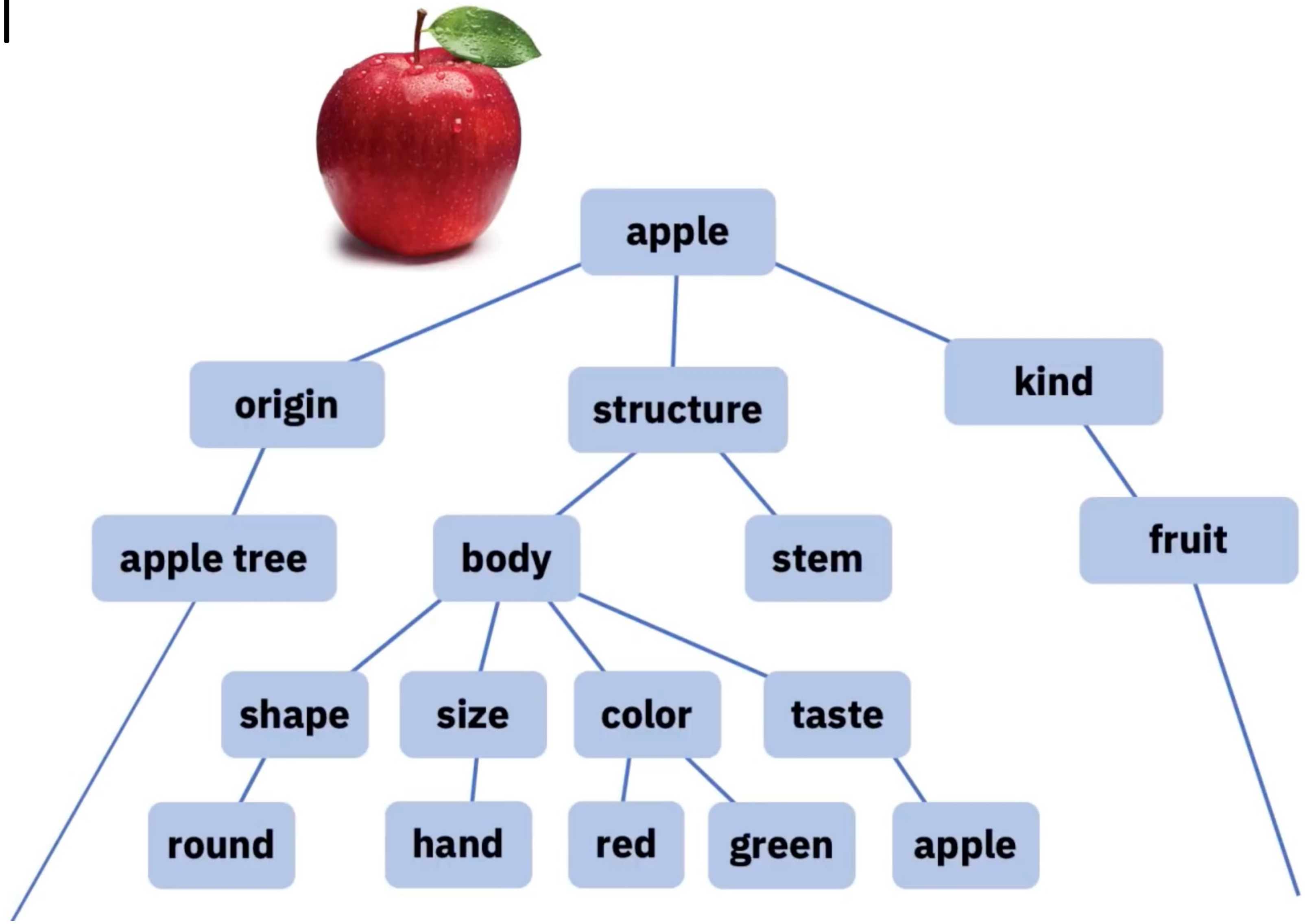
Towards Cognitive and Trustworthy AI Systems

Neural Network



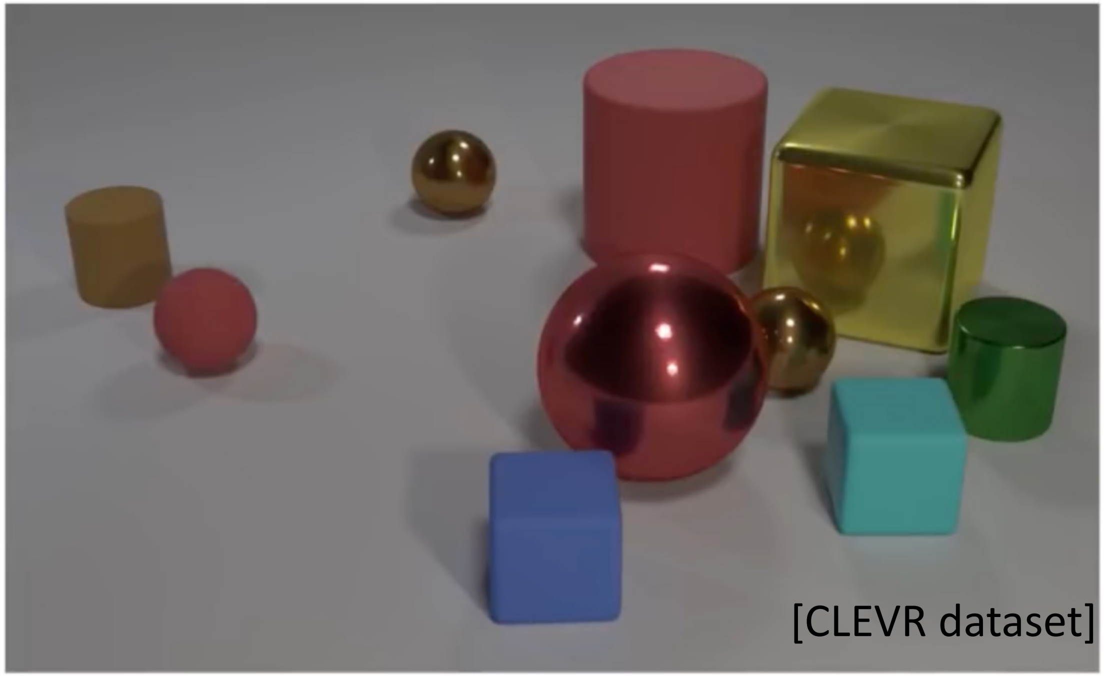
Slide Adapted from MIT 6.S191: Neurosymbolic AI

Symbolic AI



Slide Adapted from MIT 6.S191: Neurosymbolic AI

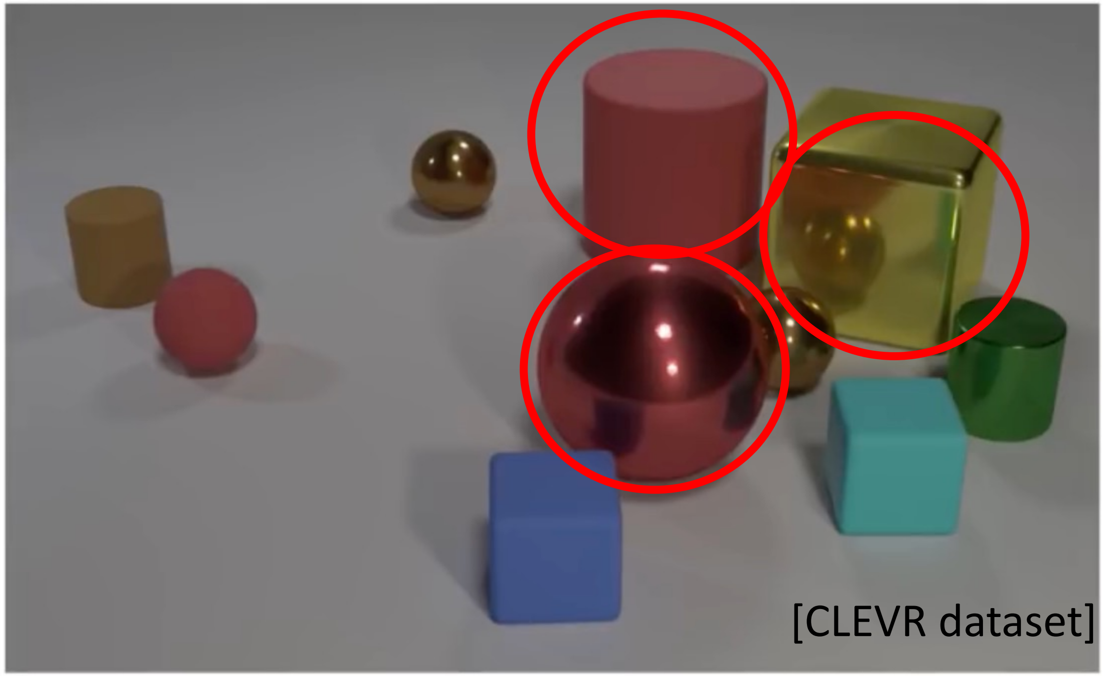
Neuro-Symbolic AI Example: Visual Reasoning



Question: *Are there an* ***equal number*** *of large things and metal spheres?*

Slide Adapted from MIT 6.S191: Neurosymbolic AI

Neuro-Symbolic AI Example: Visual Reasoning



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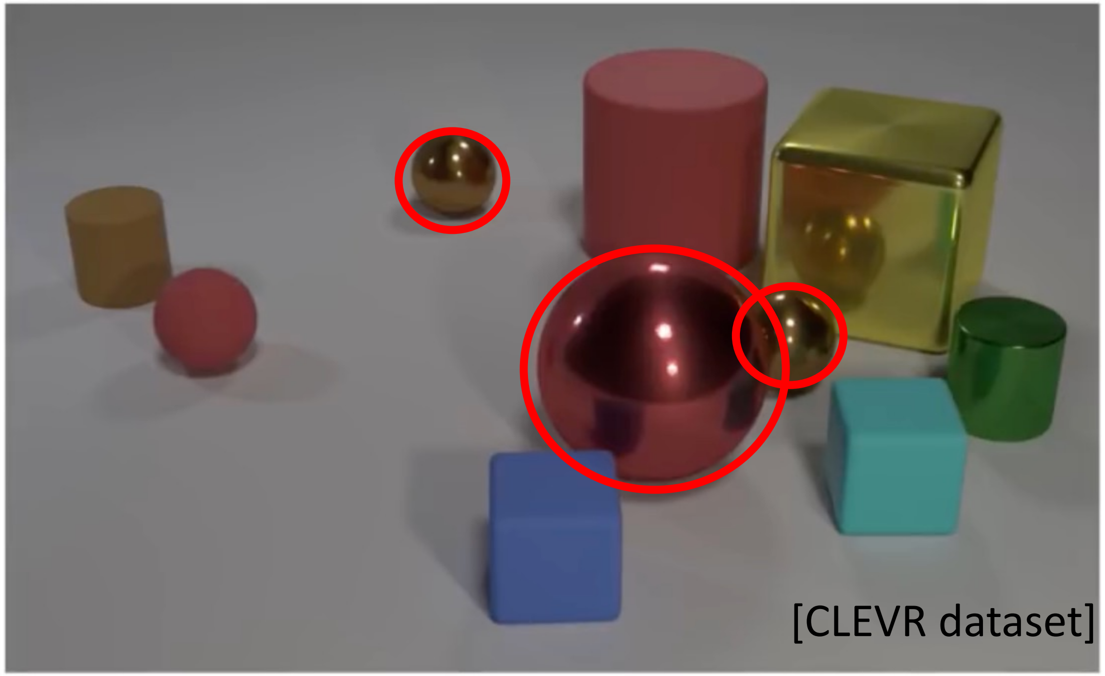

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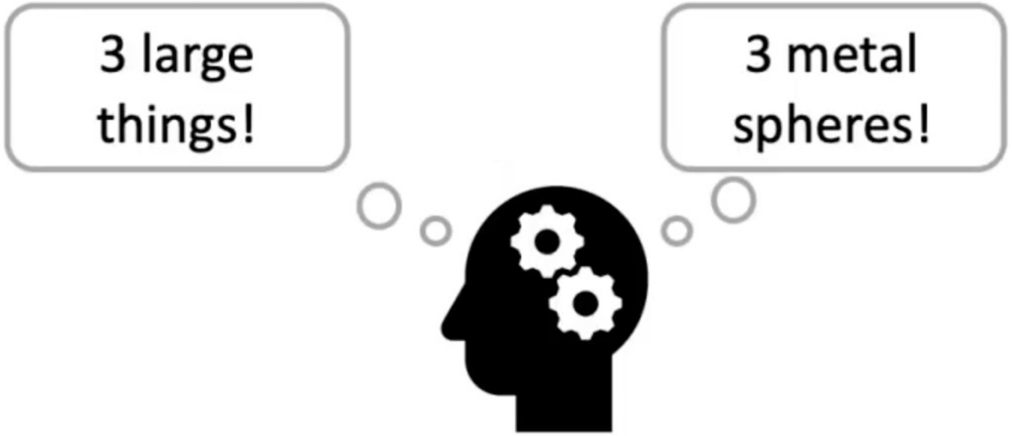

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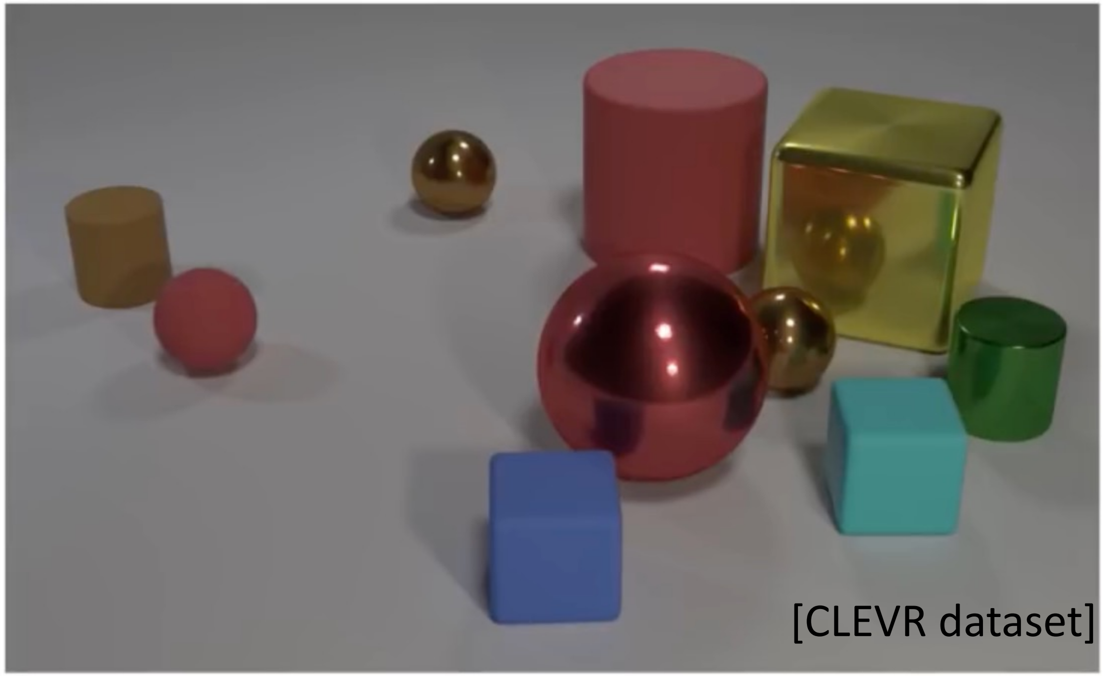

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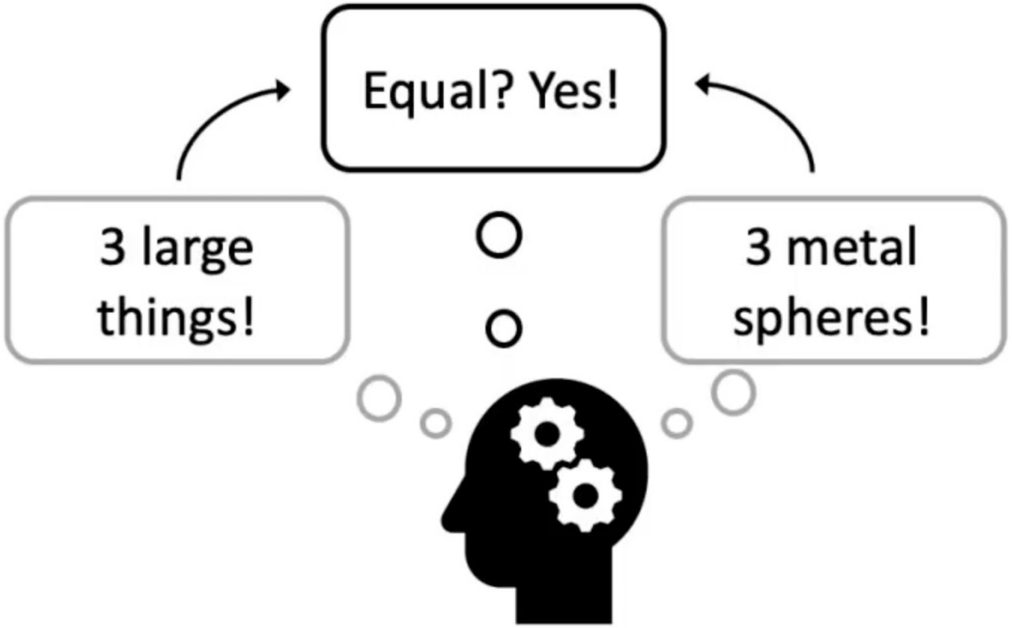

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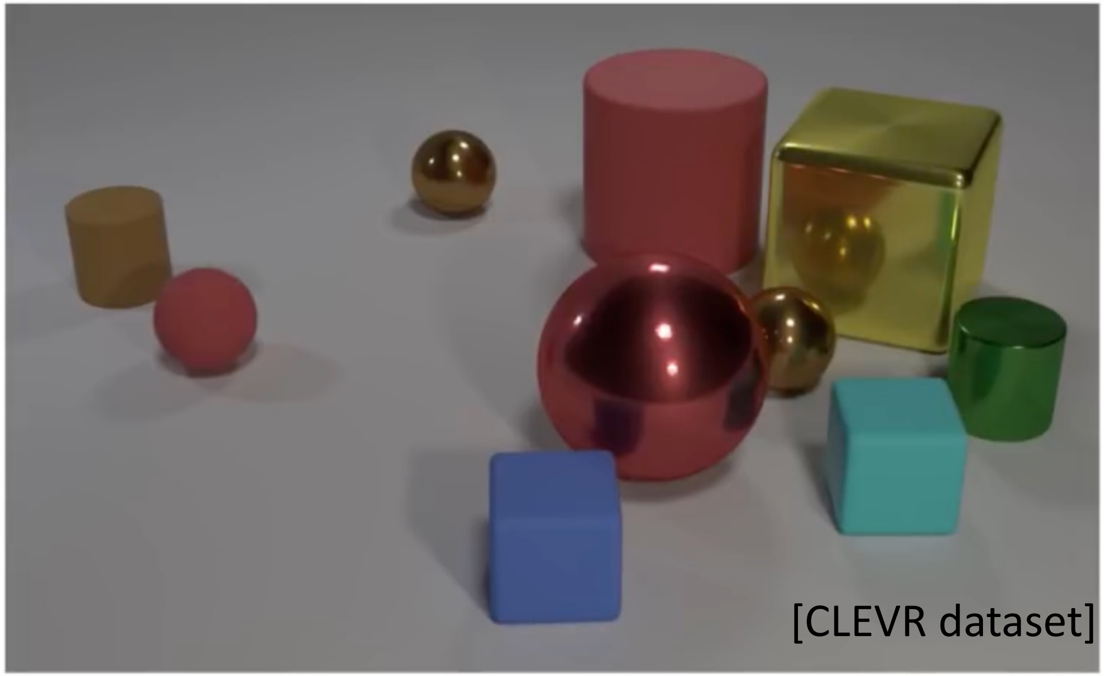
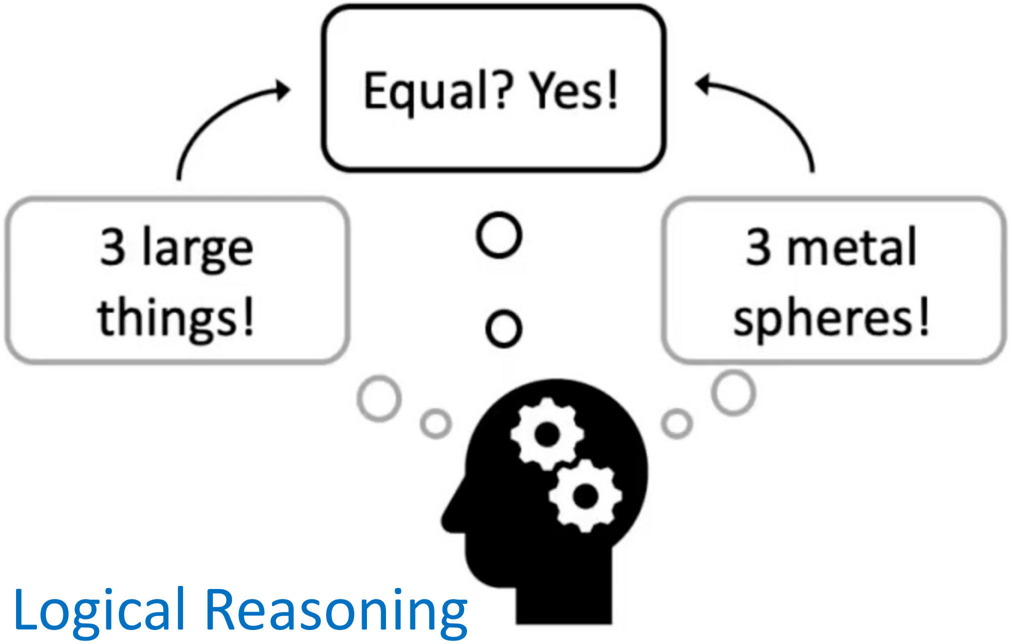
Neuro-Symbolic AI Example: Visual Reasoning



Visual Perception

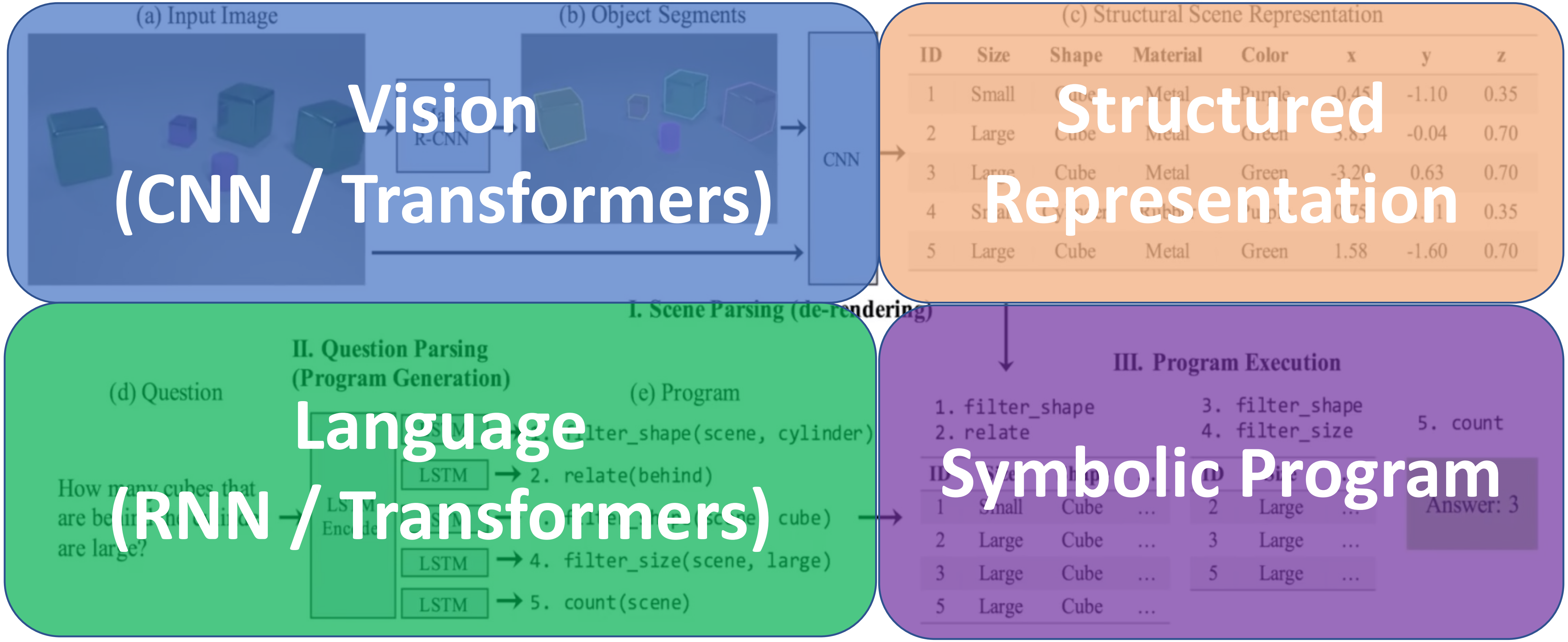
Question Understanding

Question: *Are there an **equal number** of large things and metal spheres?*



Logical Reasoning

Neuro-Symbolic AI Example: Visual Reasoning



Other Examples

Google DeepMind

AlphaGeometry: An Olympiad-level AI system for geometry

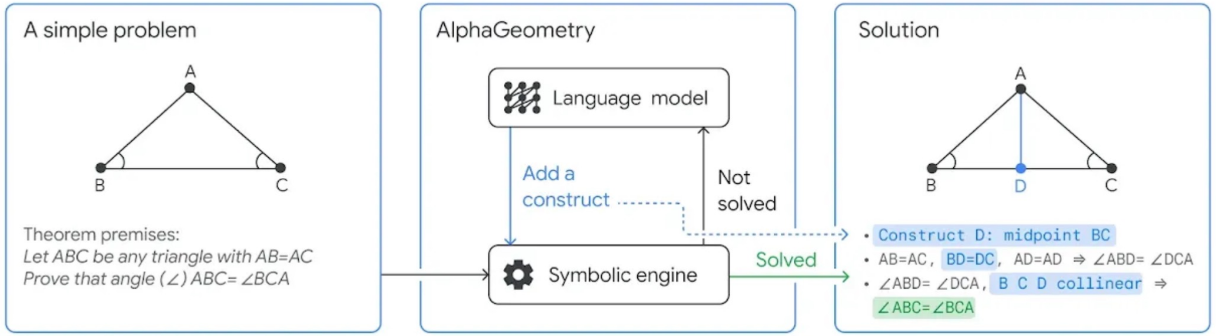
17 JANUARY 2024

Trieu Trinh and Thang Luong

Share

AlphaGeometry adopts a neuro-symbolic approach

AlphaGeometry is a neuro-symbolic system made up of a neural language model and a symbolic deduction engine, which work together to find proofs for complex geometry theorems. Akin to the idea of "thinking, fast and slow", one system provides fast, "intuitive" ideas, and the other, more deliberate, rational decision-making.



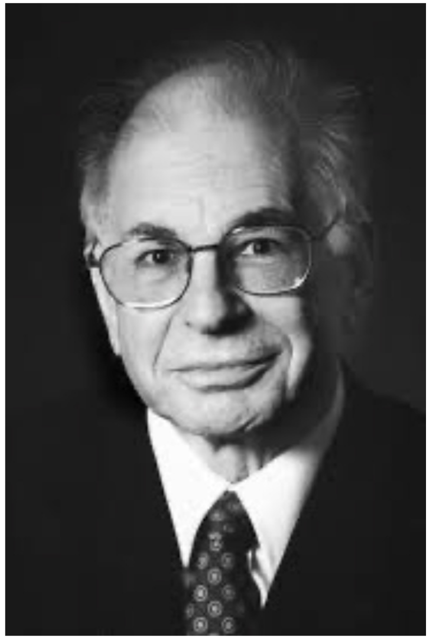
LLM: construct auxiliary points and lines
Symbolic: deductive reasoning

Eval on 30 Int. Math Olympics (IMO) problems:

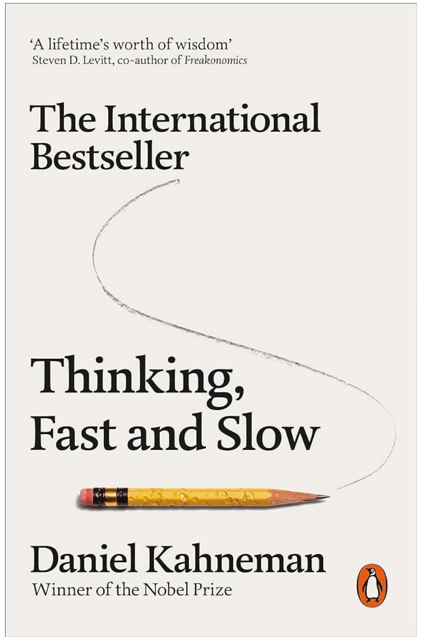
- GPT-4: 0/30
- AlphaGeometry (Neuro-Symbolic): 25/30
- Human Gold Medalist: 26/30

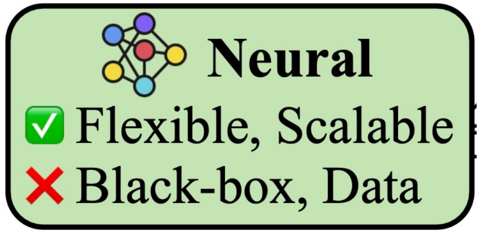
Trinh et al, "Solving Olympiad Geometry without Human Demonstrations", Nature 2024

Relationship to Human Minds



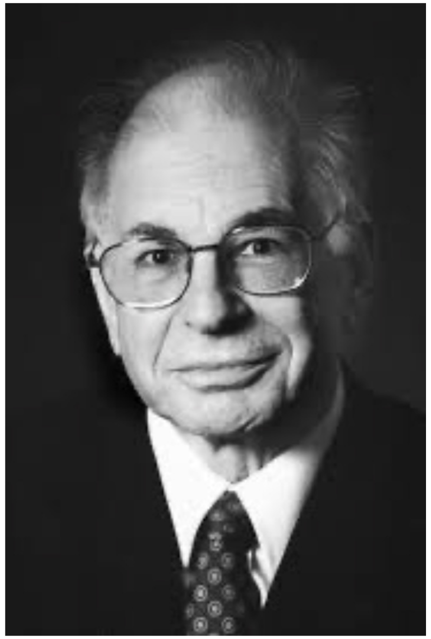
Daniel Kahneman (1934-2024)





*System 1: thinking **fast***
(intuitive perception)

Relationship to Human Minds



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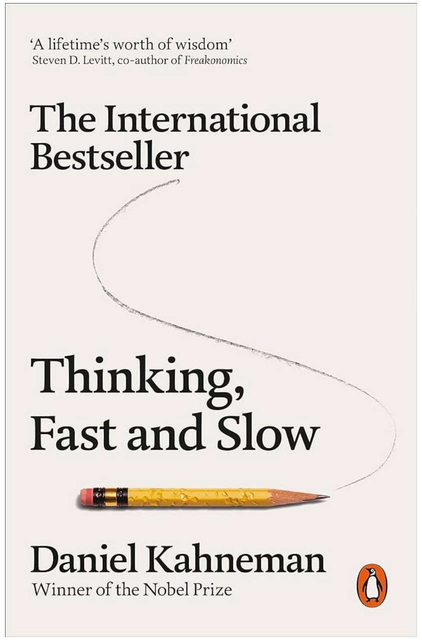


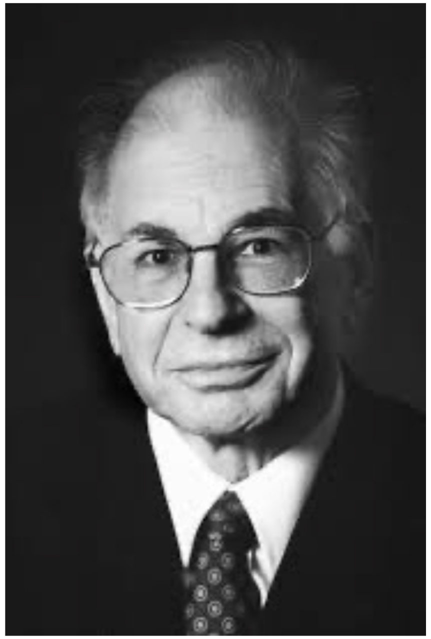
Neural
✅ Flexible, Scalable
❌ Black-box, Data

*System 1: thinking **fast***
(intuitive perception)

Symbolic
✅ Reasoning, Transparent
❌ Scalable, Learnable

*System 2: thinking **slow***
(logical reasoning)

Relationship to Human Minds



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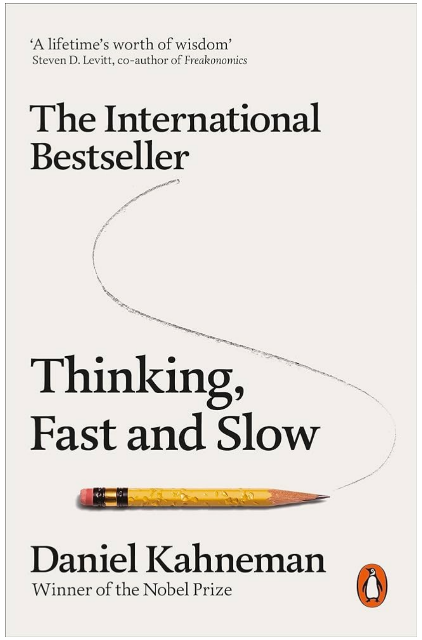
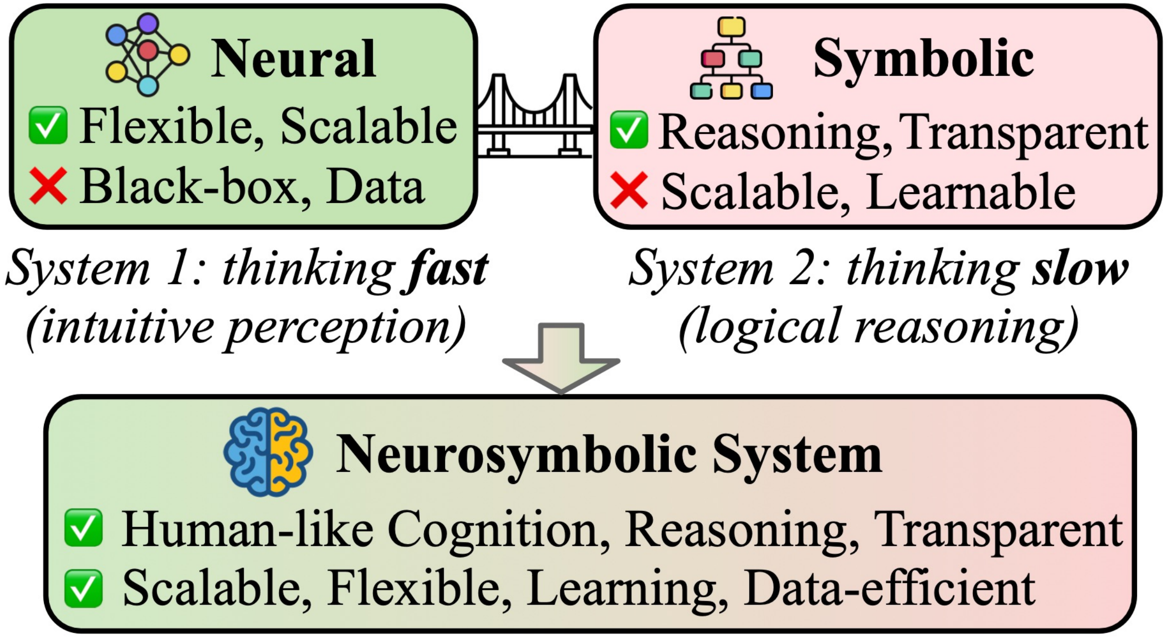
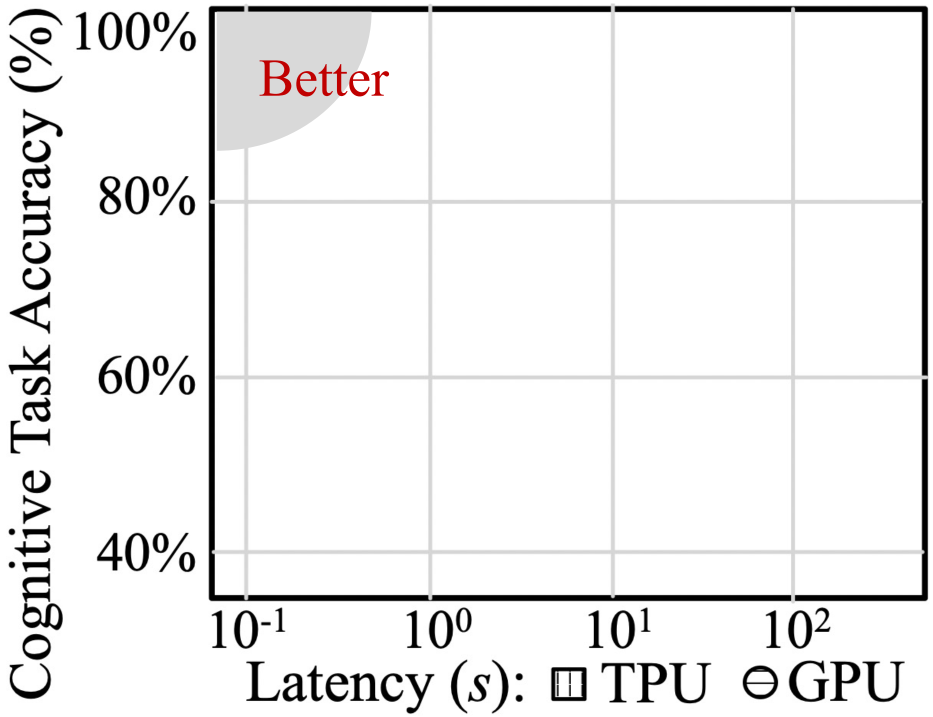
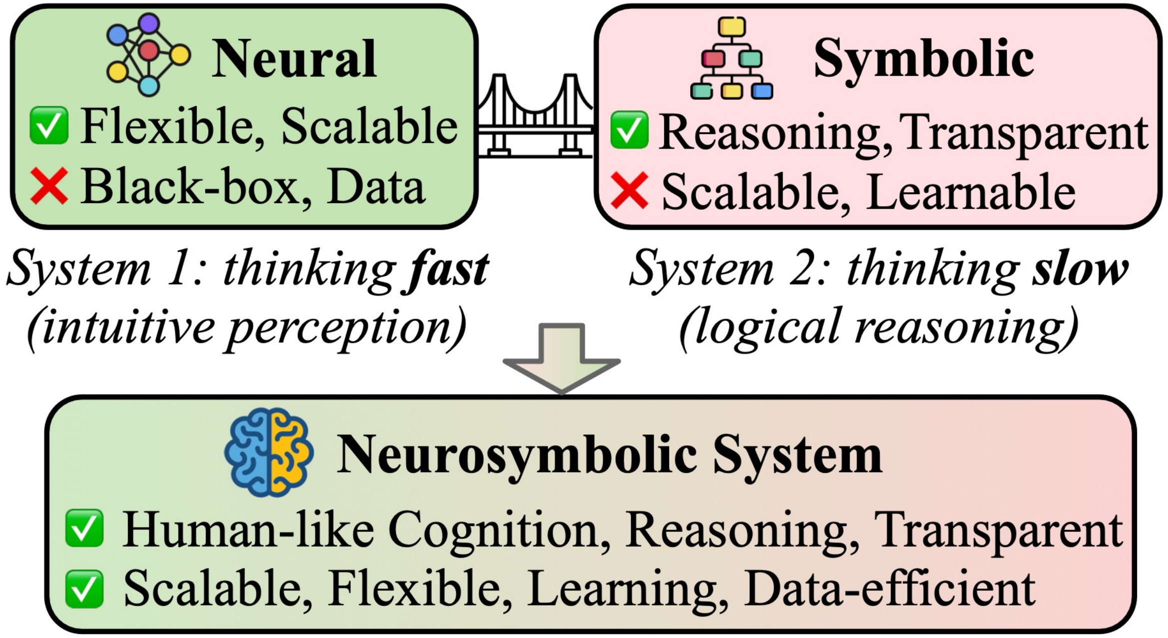




However.. From Computing Perspective





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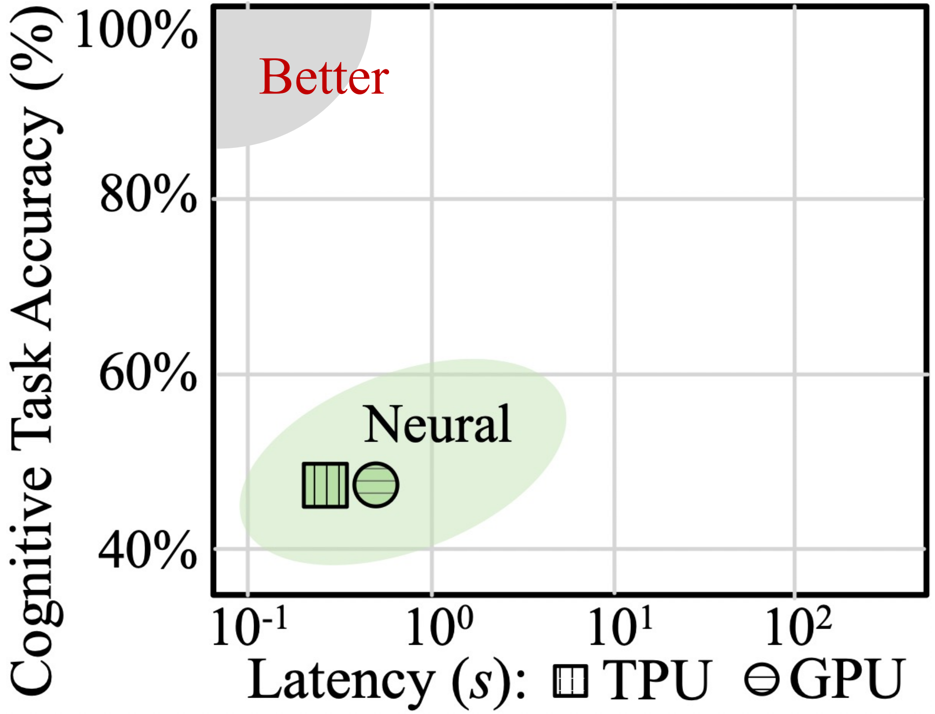

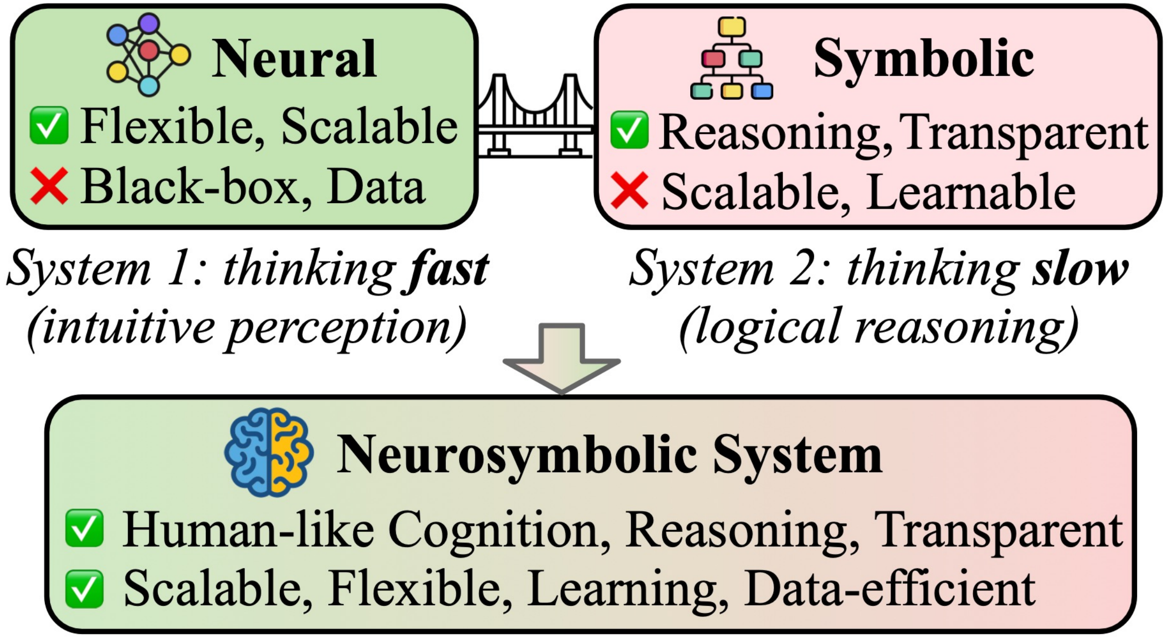

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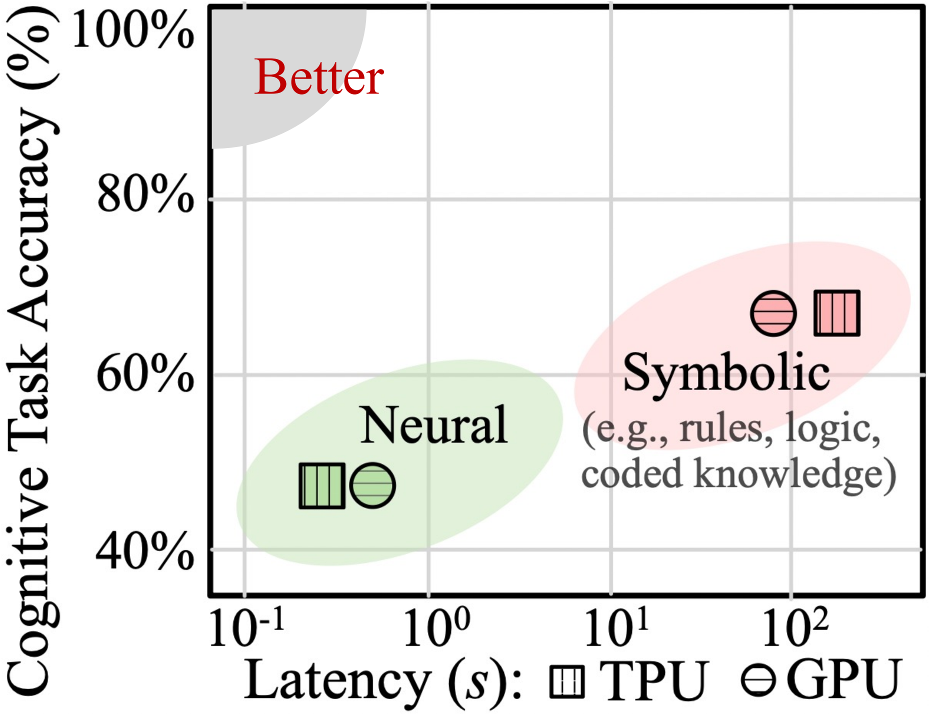

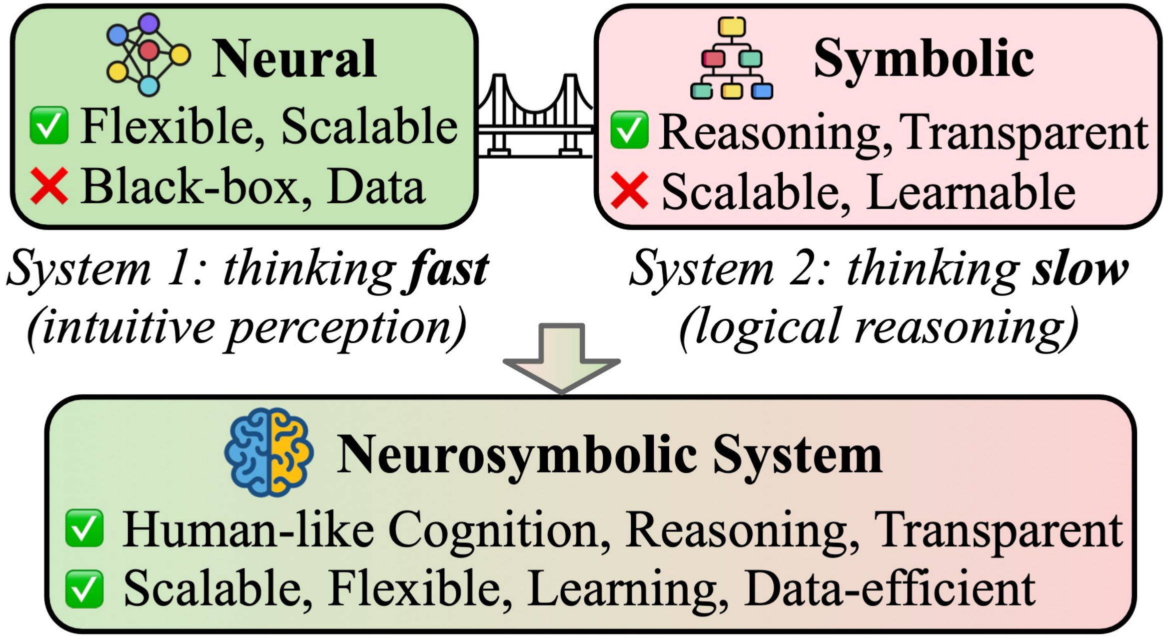

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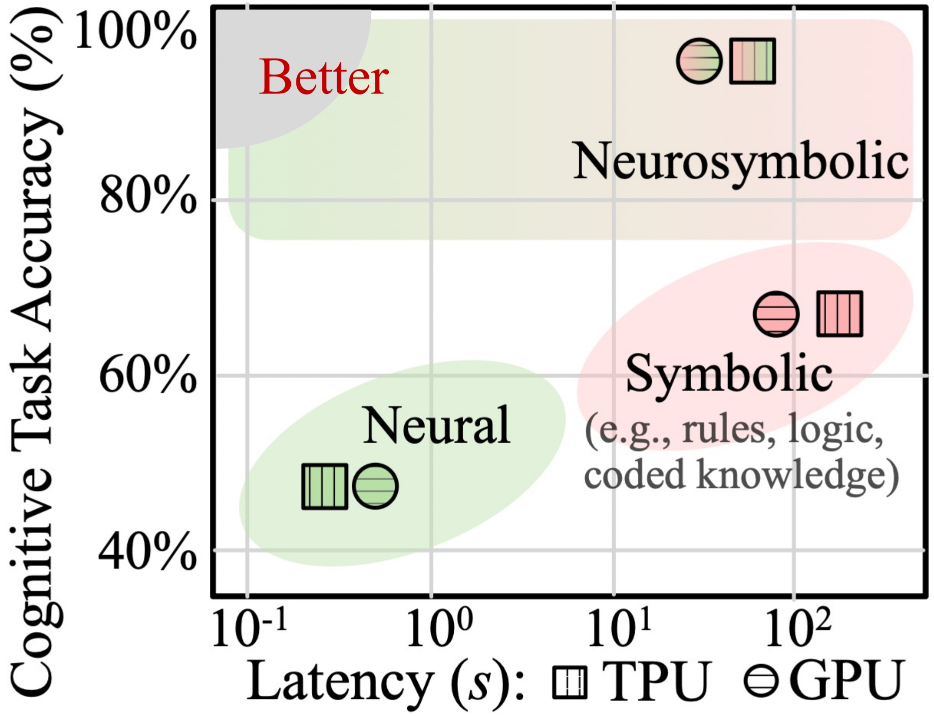
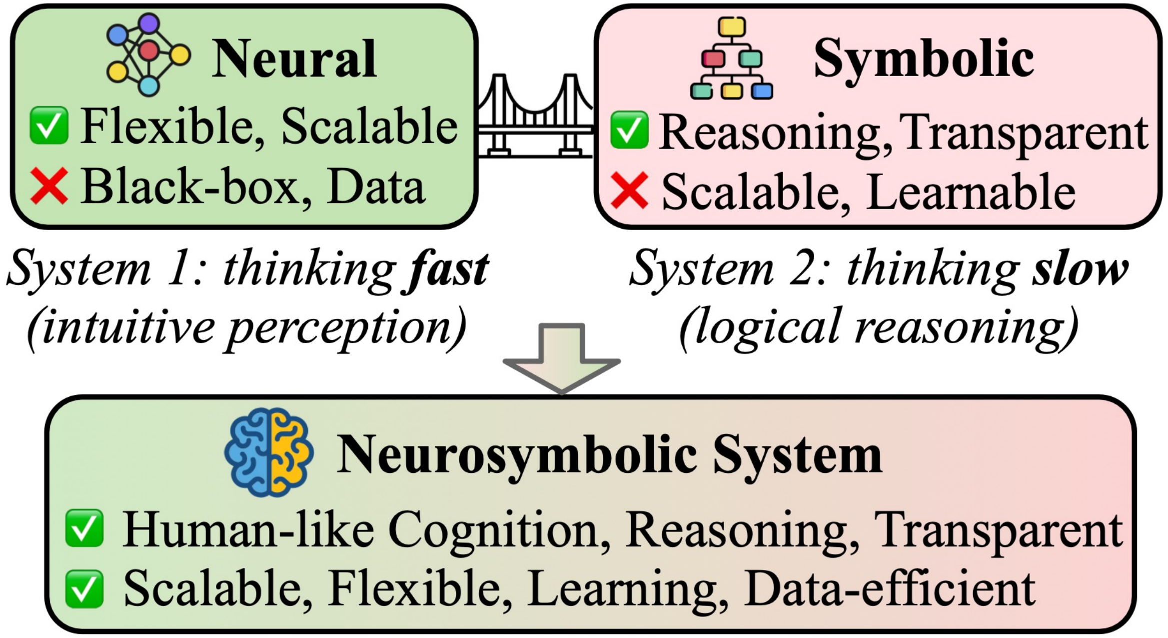


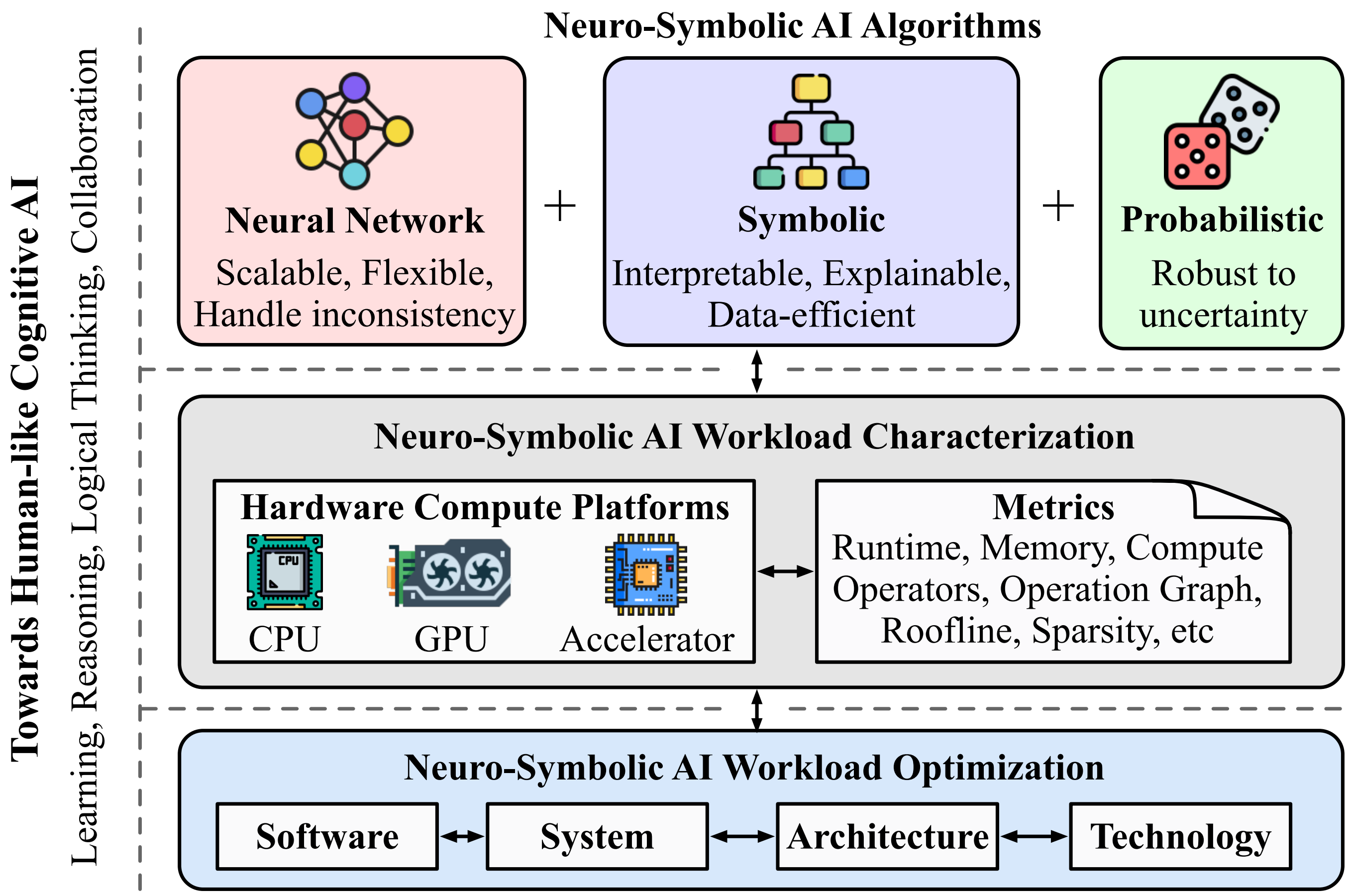


This talk: Demystify Neuro-Symbolic AI for SW/HW Co-Design

Characterize Neuro-Symbolic Workloads

Identify Potential Inefficiency Reasons

Optimize Neuro-Symbolic Systems via Co-Design



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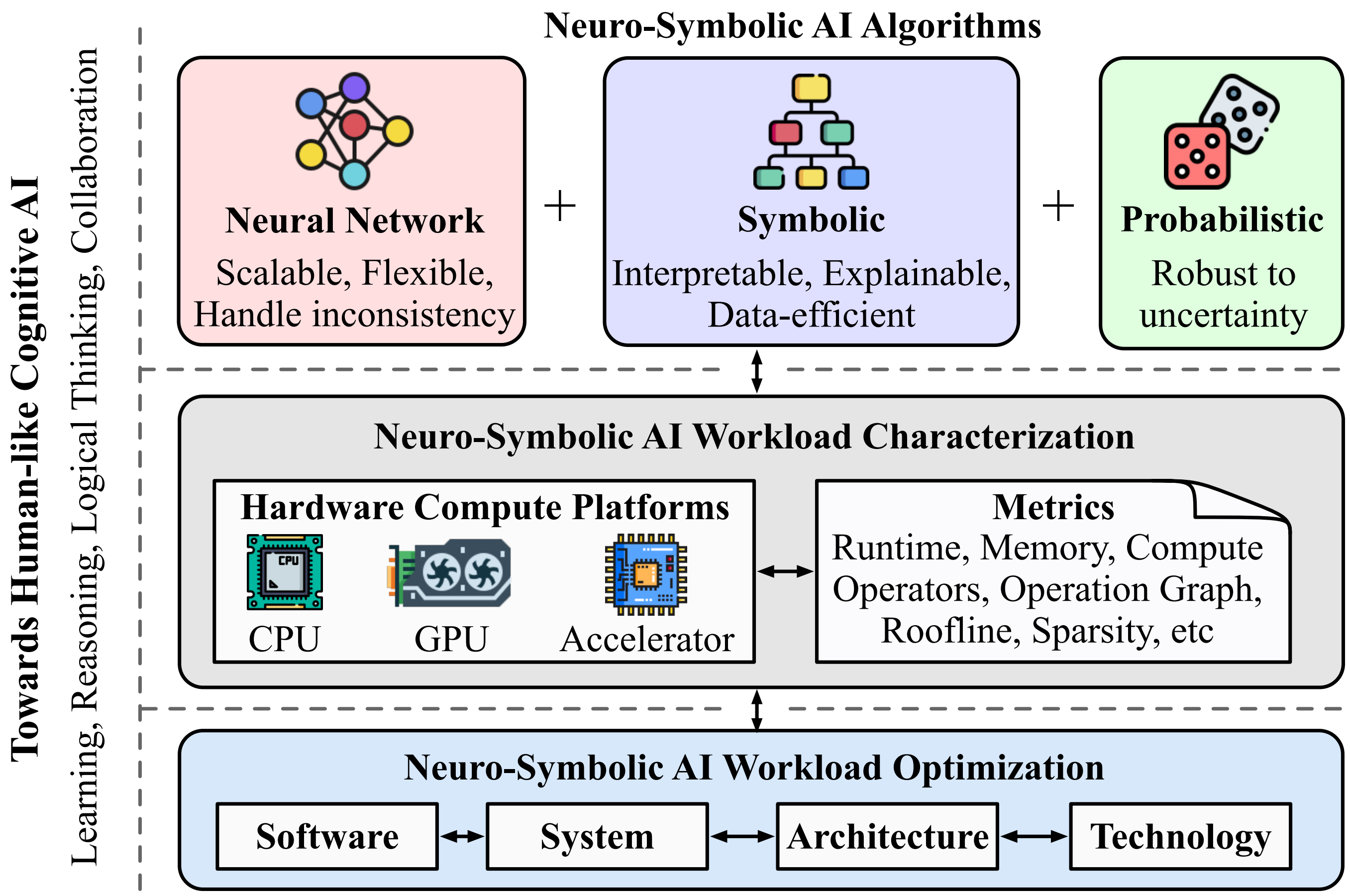
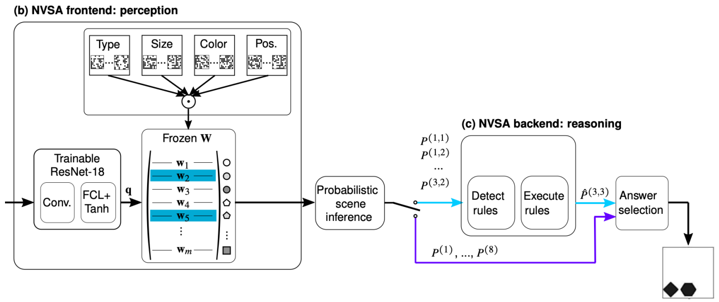
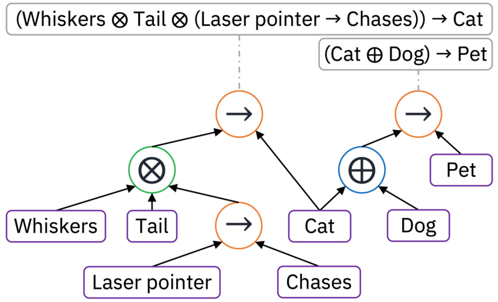


Zishen Wan, Che-Kai Liu, Hanchen Yang, Ritik Raj, Chaojian Li, Haoran You, Yonggan Fu, Cheng Wan, Ananda Samajdar, Celine Lin, Tushar Krishna, Arijit Raychowdhury, **"Workload and Characterization of Neuro-Symbolic AI"**, *in ISPASS 2024*

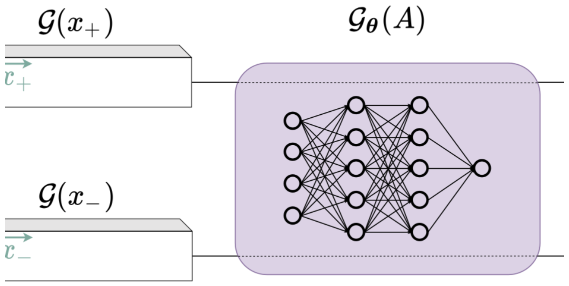
Lots of Neuro-Symbolic Algorithms



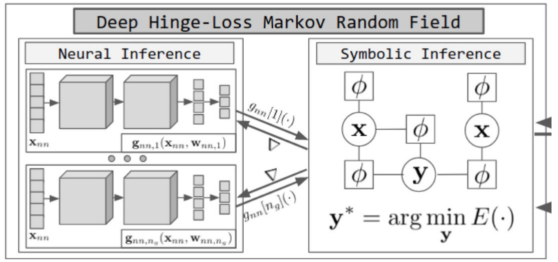
Neuro-Vector-Symbolic Arch



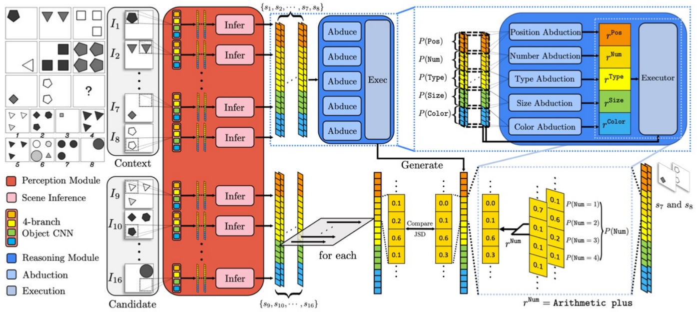
Logical Neural Network



Logical Tensor Network



Neural Probabilistic Soft Logic



Probabilistic Abduction

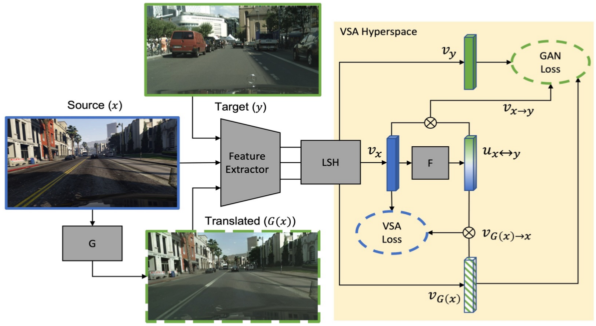
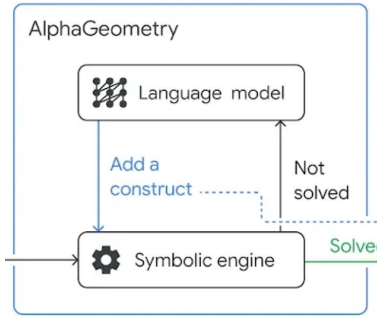
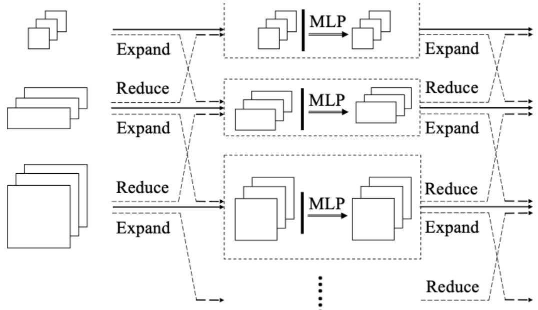


Image Translation via VSA



AlphaGeometry

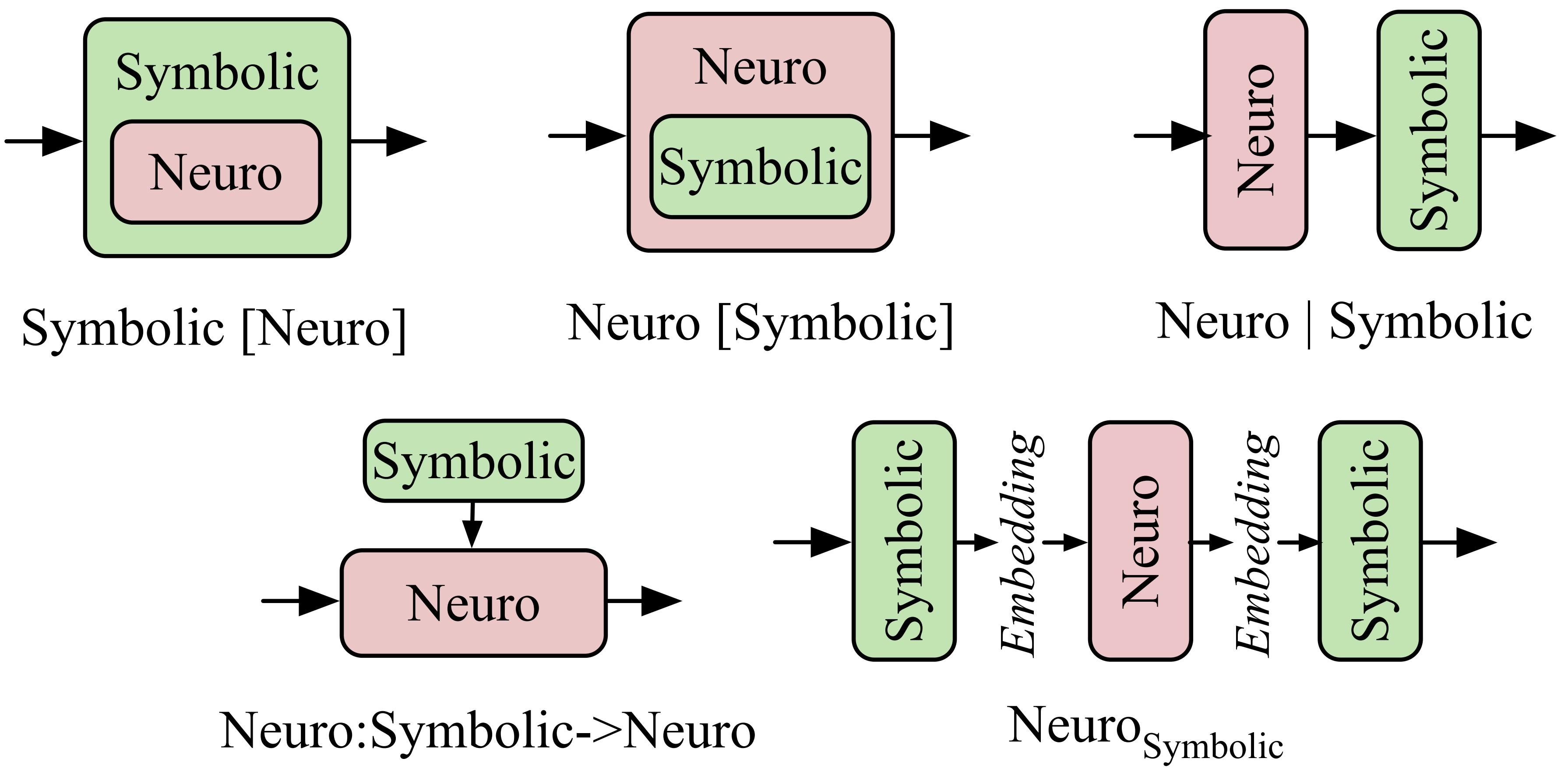


Neural Logical Machine

Neuro MLP, ConvNet, Transformer, etc

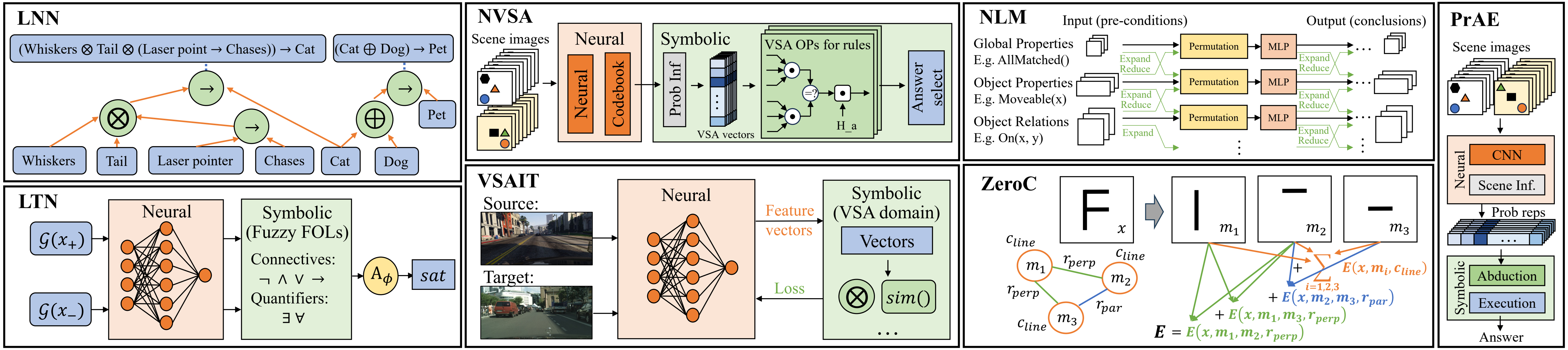
Symbolic Vector, Fuzzy logic, Knowledge graph, Decision tree, etc

Neuro-Symbolic AI Workload Category



Inspired by Henry Kautz's terminology

Selected Neuro-Symbolic Workloads



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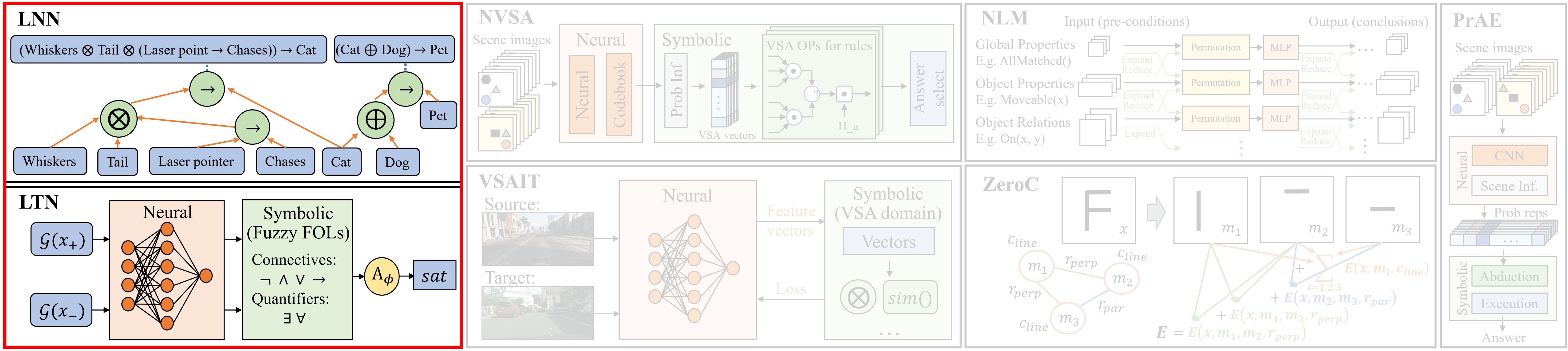
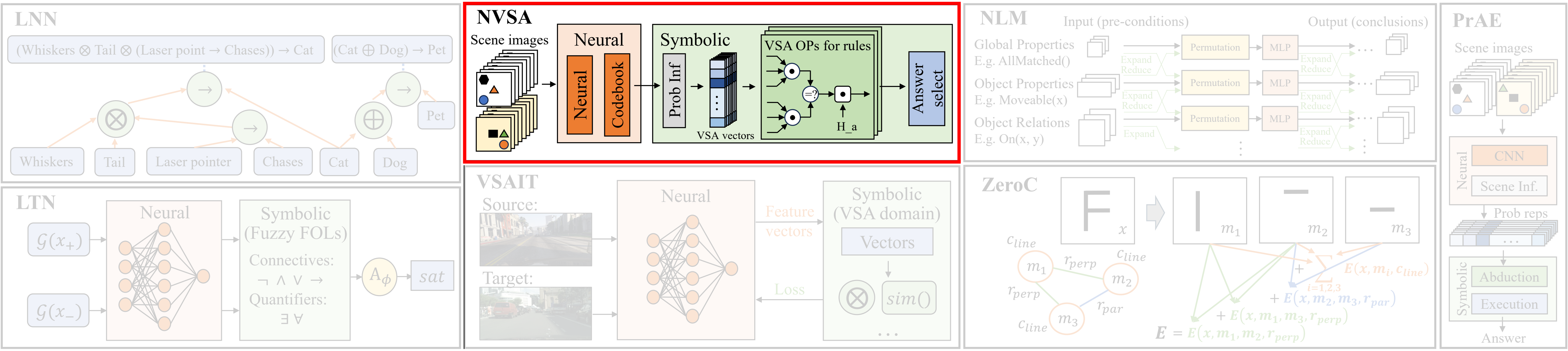


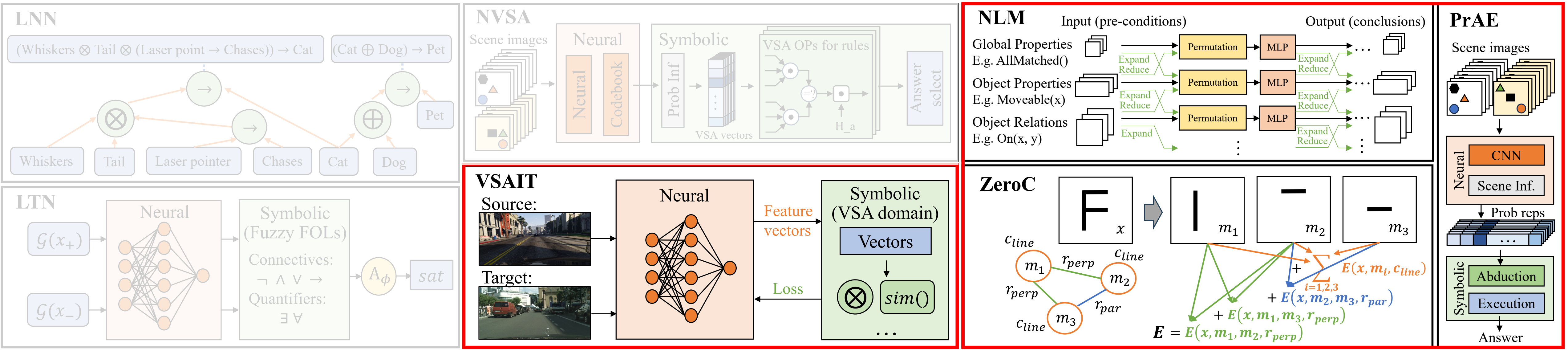
Representative Neuro-Symbolic AI Workloads		Logic Neural Network [30]	Logic Tensor Network [34]
Abbreviation		LNN	LTN
Neuro-Symbolic Category		Neuro:Symbolic→Neuro	Neuro$_{\text{Symbolic}}$
Learning Approach		Supervised	Supervised/Unsupervised
Deployment Scenario	Application	Learning and reasoning, Full theorem prover	Querying, learning, reasoning (relational and embedding learning, query answering)
	Advantage vs. Neural Model	Higher interoperability, resilience to incomplete knowledge, generalization	Higher data efficiency, comprehensibility, out-of-distribution generalization
	Dataset	LUBM benchmark [40], TPTP benchmark [41]	UCI [42], Leptograpsus crabs [43], DeepProbLog [44]
Computation Pattern	Datatype	FP32	FP32
	Neuro	Graph	MLP
	Symbolic	FOL/Logical operation	FOL/Logical operation

Selected Neuro-Symbolic Workloads



Representative Neuro-Symbolic AI Workloads		Logic Neural Network [30]	Logic Tensor Network [34]	Neuro-Vector-Symbolic Architecture [4]
Abbreviation		LNN	LTN	NVSA
Neuro-Symbolic Category		Neuro:Symbolic→Neuro	Neuro$_{\text{Symbolic}}$	Neuro|Symbolic
Learning Approach		Supervised	Supervised/Unsupervised	Supervised/Unsupervised
Deployment Scenario	Application	Learning and reasoning, Full theorem prover	Querying, learning, reasoning (relational and embedding learning, query answering)	Fluid intelligence, Abstract reasoning
	Advantage vs. Neural Model	Higher interoperability, resilience to incomplete knowledge, generalization	Higher data efficiency, comprehensibility, out-of-distribution generalization	Higher joint representations efficiency, abstract reasoning capability, transparency
	Dataset	LUBM benchmark [40], TPTP benchmark [41]	UCI [42], Leptograpsus crabs [43], DeepProbLog [44]	RAVEN [21], I-RAVEN [22], PGM [45]
Computation Pattern	Datatype	FP32	FP32	FP32
	Neuro	Graph	MLP	ConvNet
	Symbolic	FOL/Logical operation	FOL/Logical operation	VSA/Vector operation

Selected Neuro-Symbolic Workloads



Representative Neuro-Symbolic AI Workloads		Logic Neural Network [30]	Logic Tensor Network [34]	Neuro-Vector-Symbolic Architecture [4]	Vector Symbolic Architecture Image2Image Translation [7]	Neural Logic Machine [38]	Zero-shot Concept Recognition and Acquisition [37]	Probabilistic Abduction and Execution [23]
Abbreviation		LNN	LTN	NVSA	VSAIT	NLM	ZeroC	PrAE
Neuro-Symbolic Category		Neuro:Symbolic→Neuro	$\text{Neuro}_{\text{Symbolic}}$	Neuro|Symbolic	Neuro|Symbolic	Neuro[Symbolic]	Neuro[Symbolic]	Neuro|Symbolic
Learning Approach		Supervised	Supervised/Unsupervised	Supervised/Unsupervised	Supervised	Supervised/Unsupervised	Supervised	Supervised/Unsupervised
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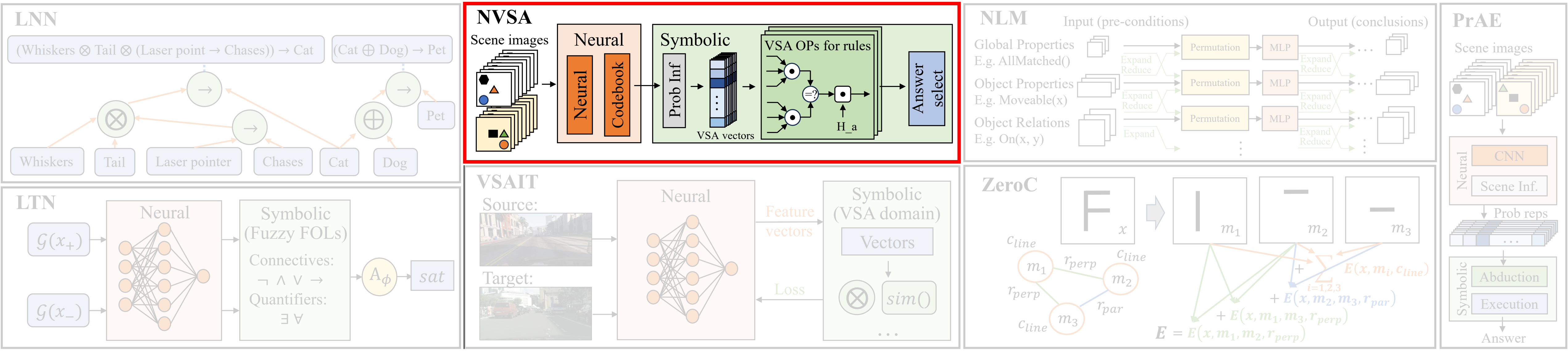
	Symbolic	FOL/Logical operation	FOL/Logical operation	VSA/Vector operation	VSA/Vector operation	FOL/Logical operation	Graph, vector operation	VSA/Vector operation

Example: Neuro-Vector-Symbolic Architecture (NVSA)



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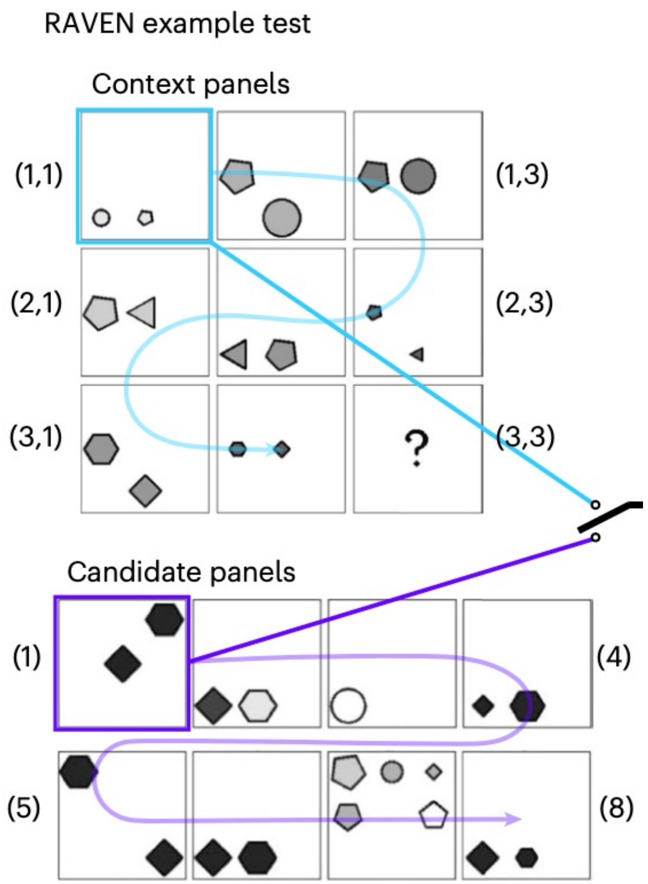
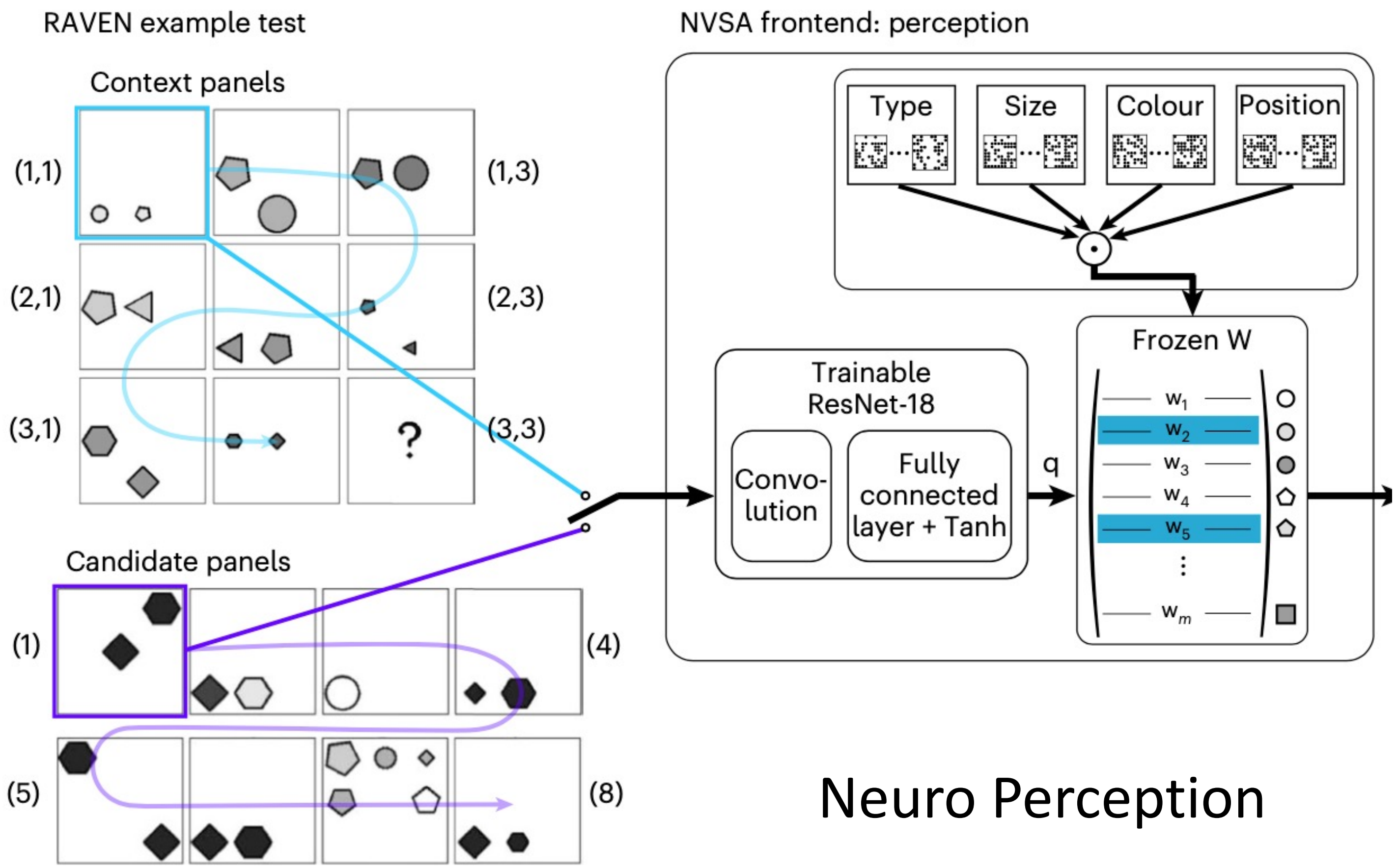


Hersche, et al. “*A neuro-vector-symbolic architecture for solving Raven’s progressive matrices*”. In Nature Machine Intelligence, 2023

Example: Neuro-Vector-Symbolic Architecture



Neuro Perception

Hersche, et al. "*A neuro-vector-symbolic architecture for solving Raven's progressive matrices*". In Nature Machine Intelligence, 2023

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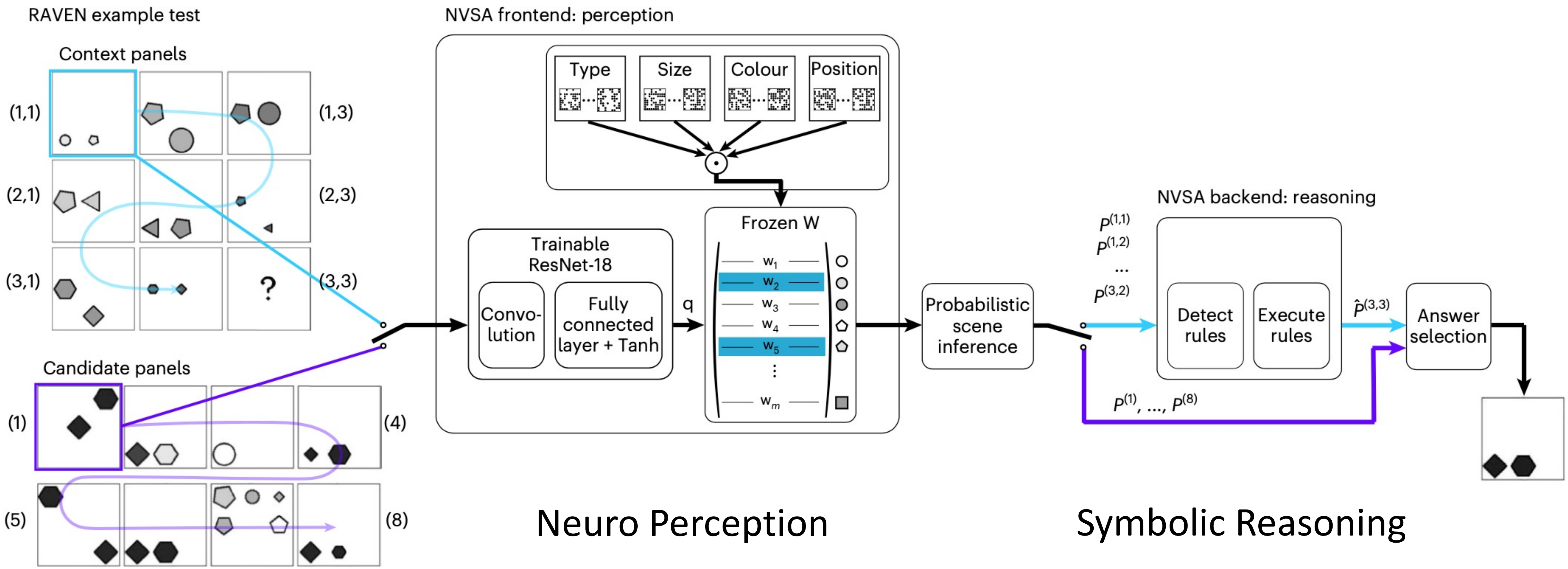


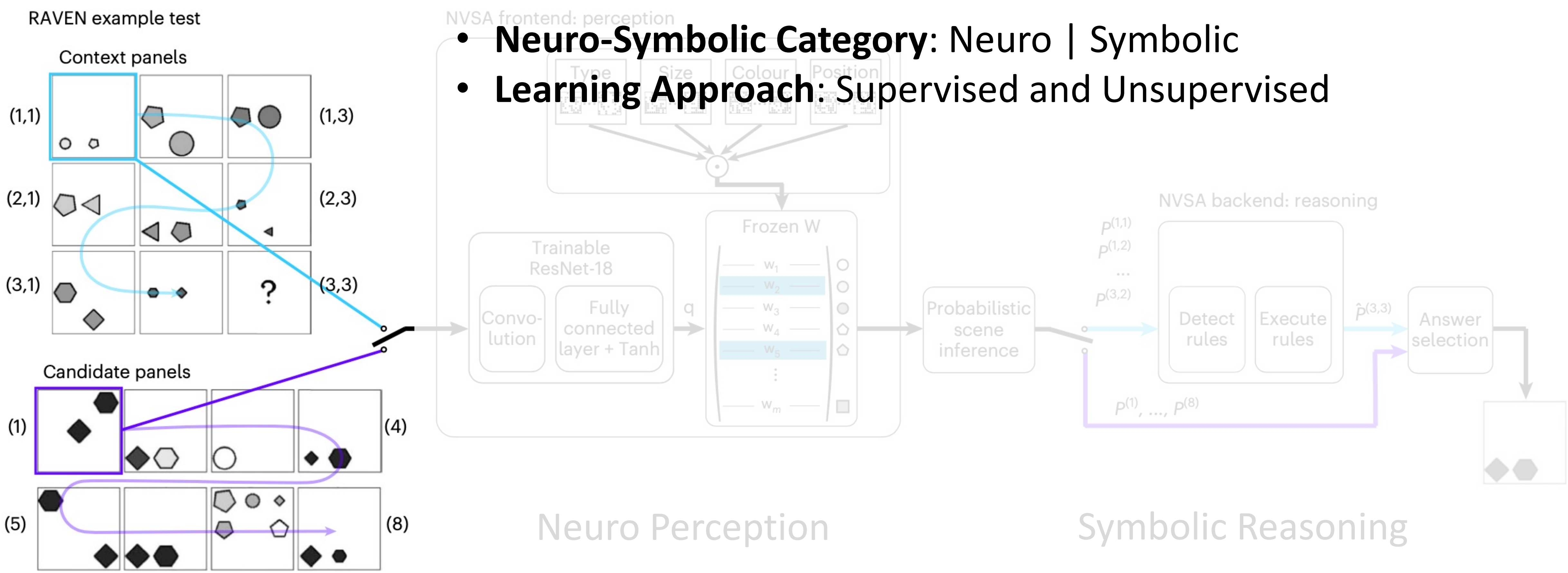
Neuro Perception

Symbolic Reasoning

Hersche, et al. "*A neuro-vector-symbolic architecture for solving Raven's progressive matrices*". In Nature Machine Intelligence, 2023

Example: Neuro-Vector-Symbolic Architecture

- **Neuro-Symbolic Category**: Neuro | Symbolic
- **Learning Approach**: Supervised and Unsupervised



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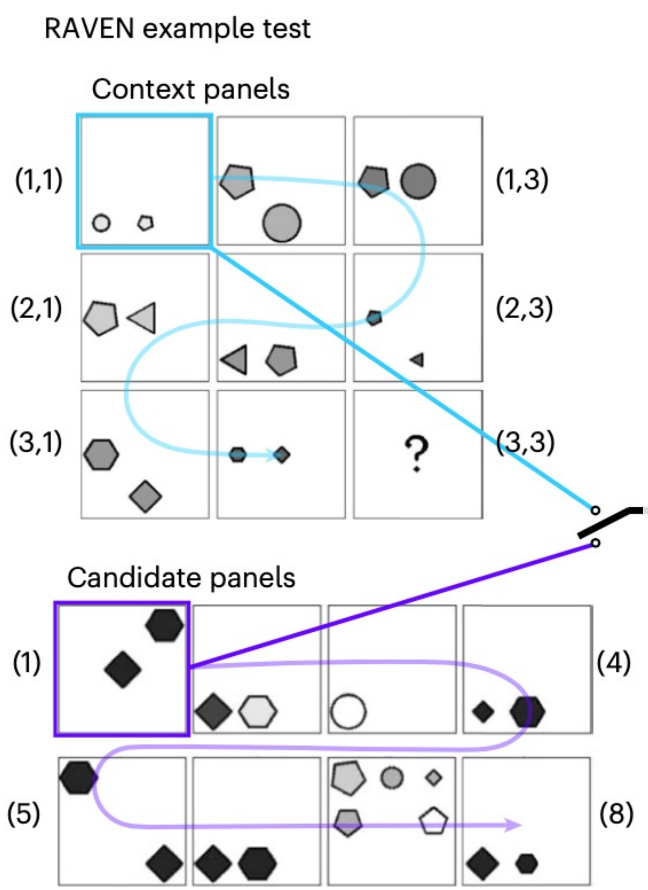

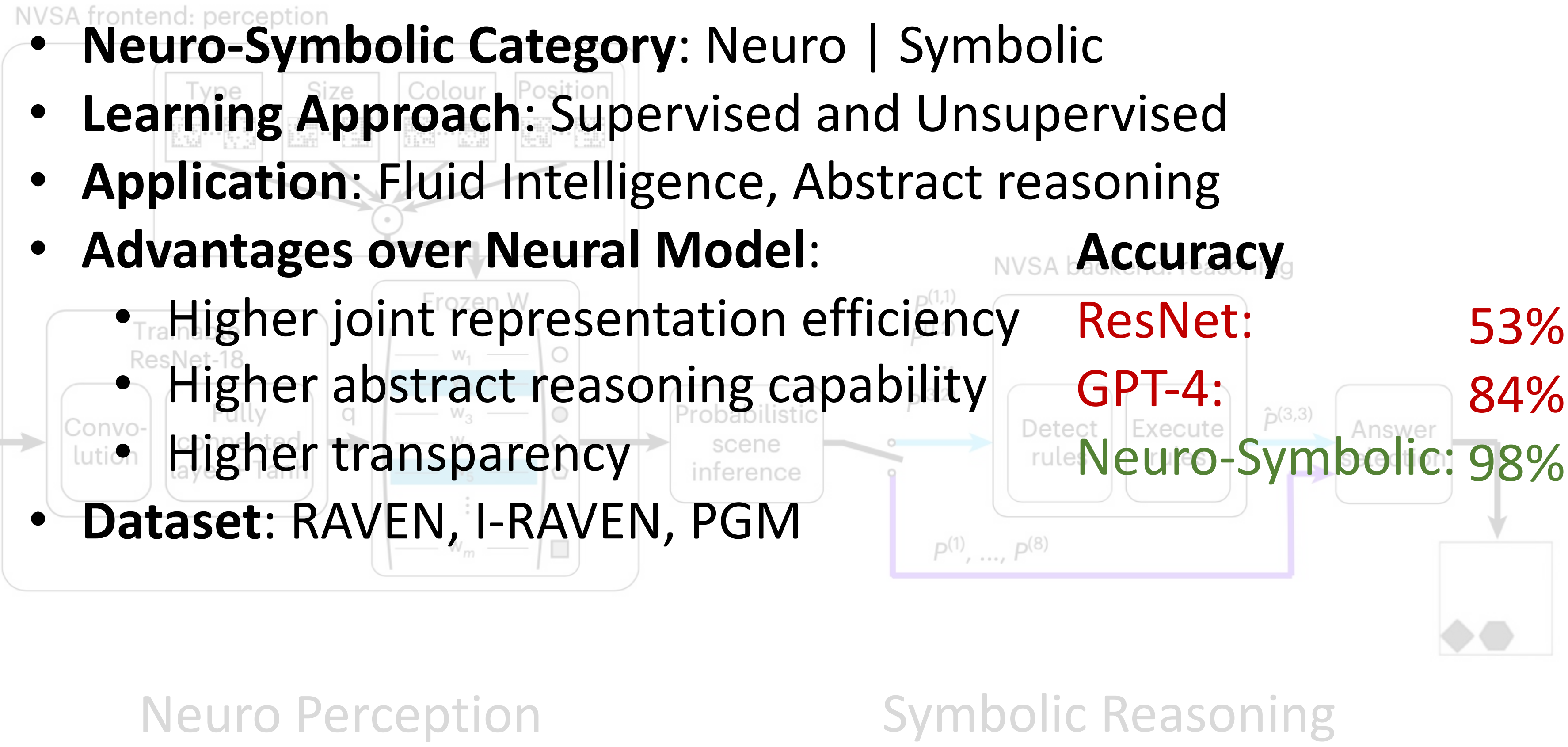

- **Neuro-Symbolic Category**: Neuro | Symbolic
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- **Application**: Fluid Intelligence, Abstract reasoning
- **Advantages over Neural Model**:
  - Higher joint representation efficiency
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  - Higher transparency
- **Dataset**: RAVEN, I-RAVEN, PGM

Accuracy	
ResNet:	53%
GPT-4:	84%
Neuro-Symbolic:	98%

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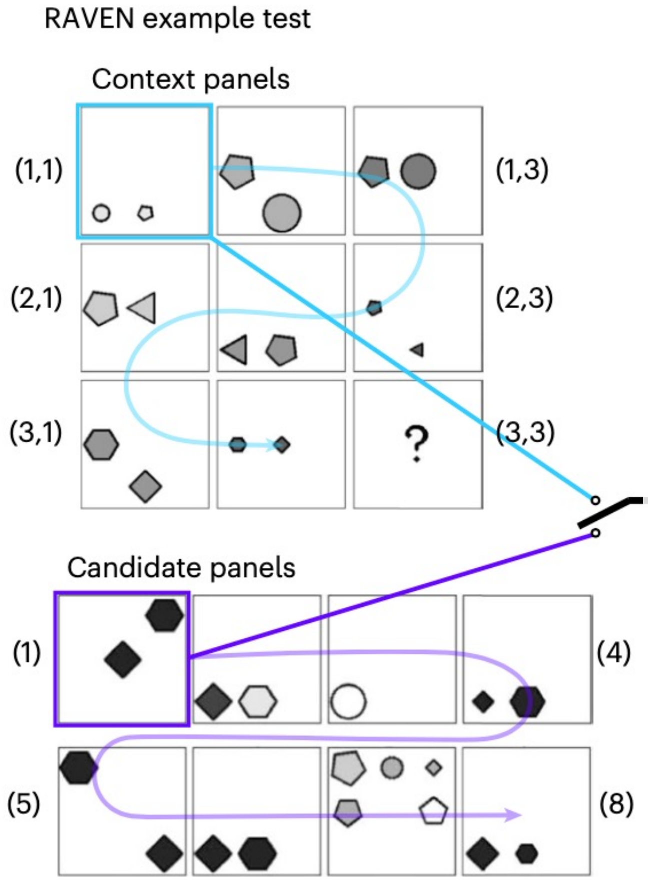

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- **Dataset**: RAVEN, I-RAVEN, PGM
- **Computational Components**:
  - Neuro: ConvNet
  - Symbolic: vector-symbolic operation, circular convolution

Accuracy

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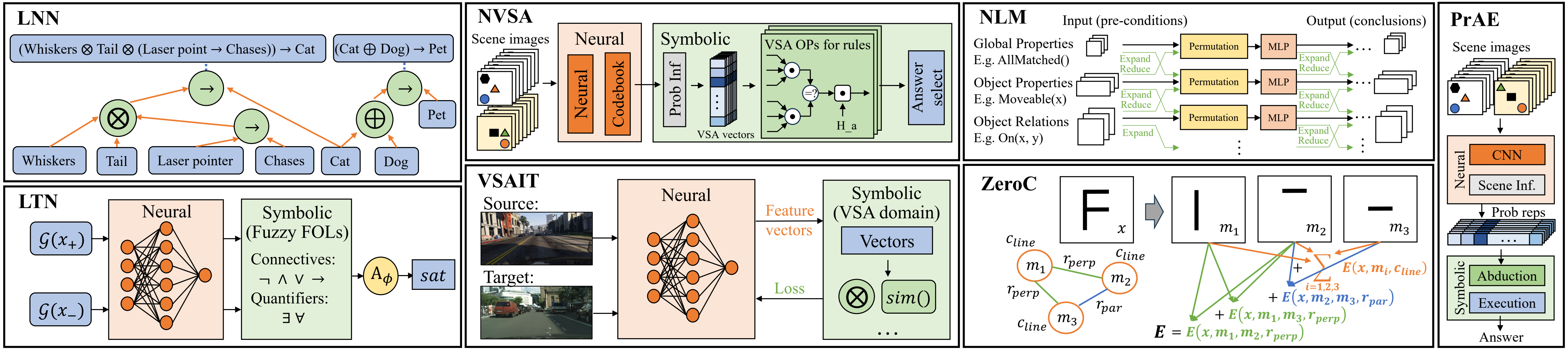

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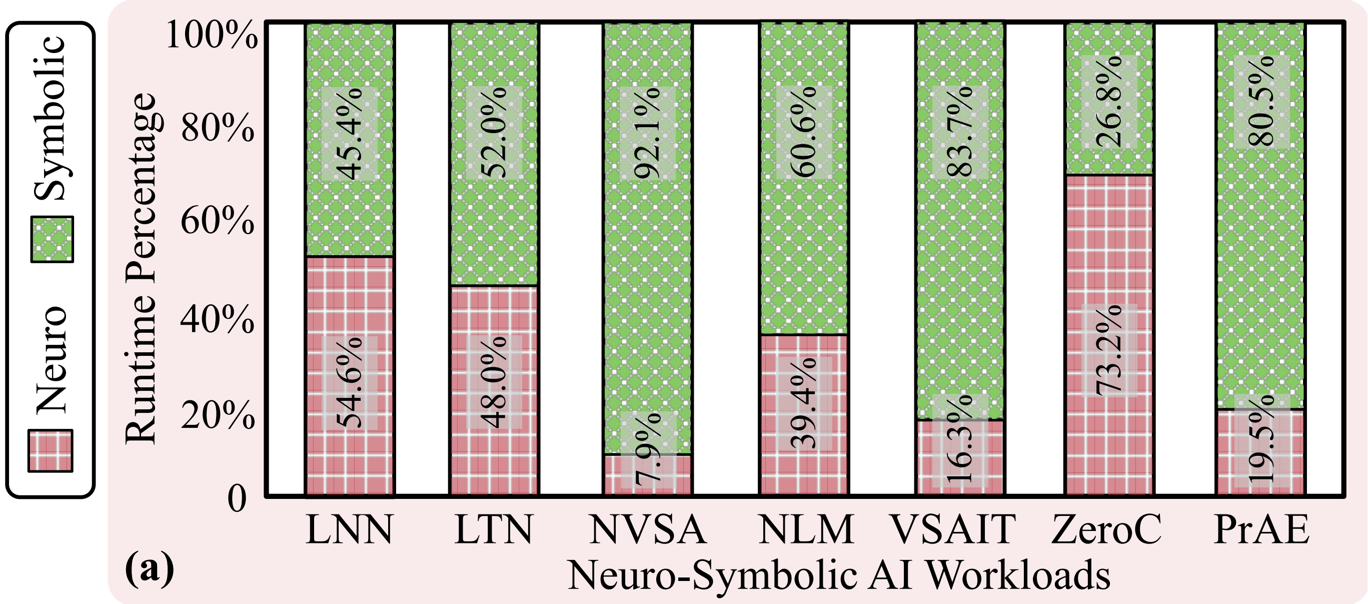
Workload Characterization - Runtime

Profiling setup: CPU+GPU system, using pytorch profiler, seven neuro-symbolic workloads

- End-to-end runtime latency analysis:



Neuro-symbolic workload exhibits **high latency** compared to neural models;

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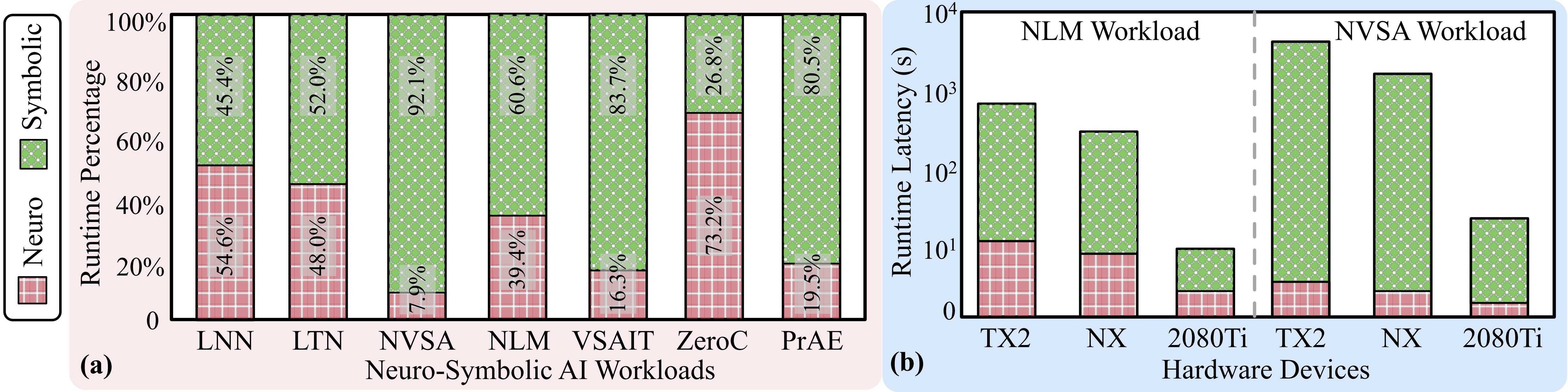
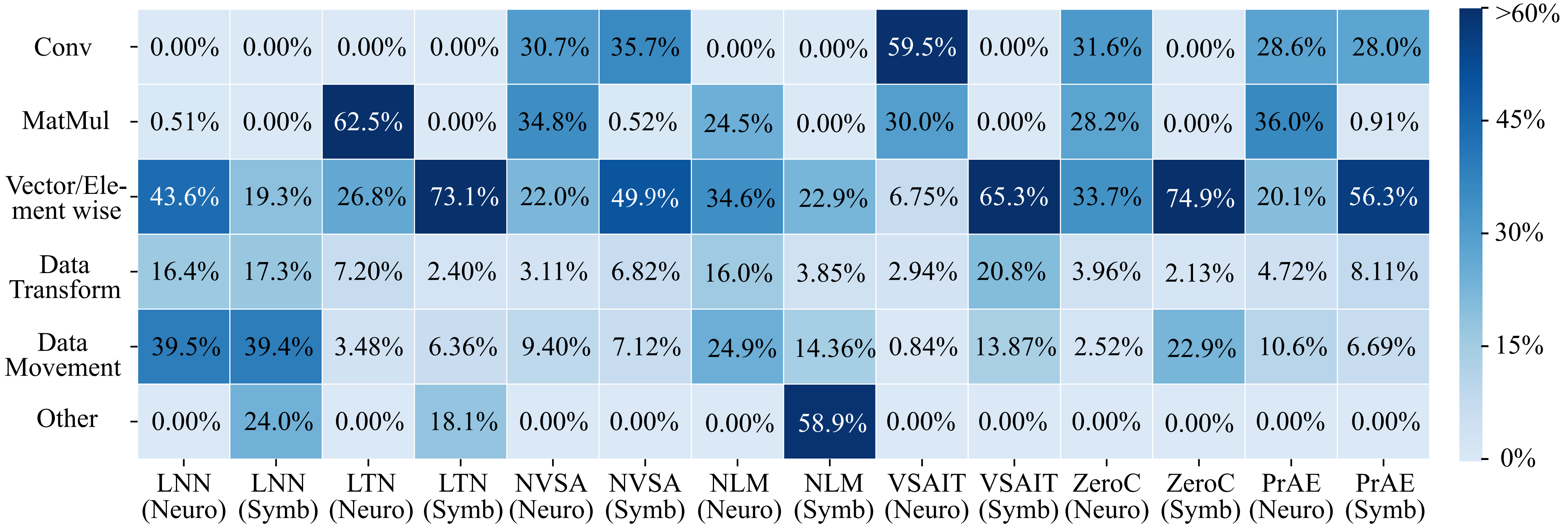


Neuro-symbolic workload exhibits **high latency** compared to neural models;
Symbolic component is executed **inefficiently** across off-the-shelf CPU/GPUs

Workload Characterization - Operator

- Compute operator analysis:



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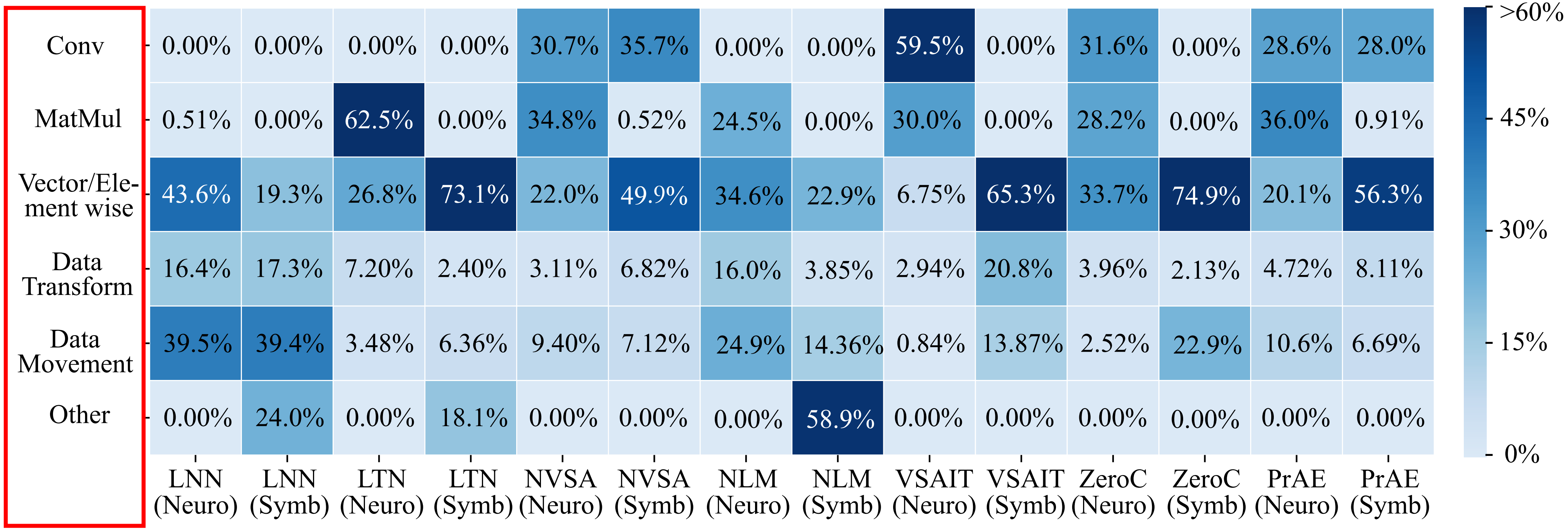

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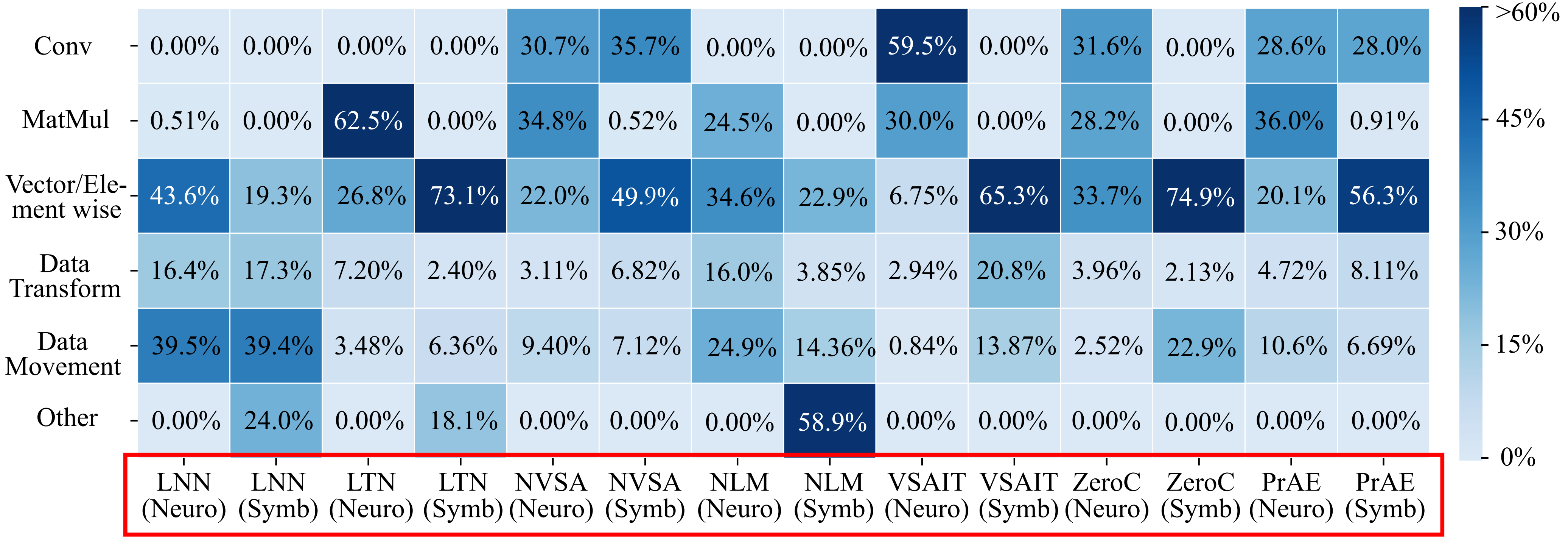

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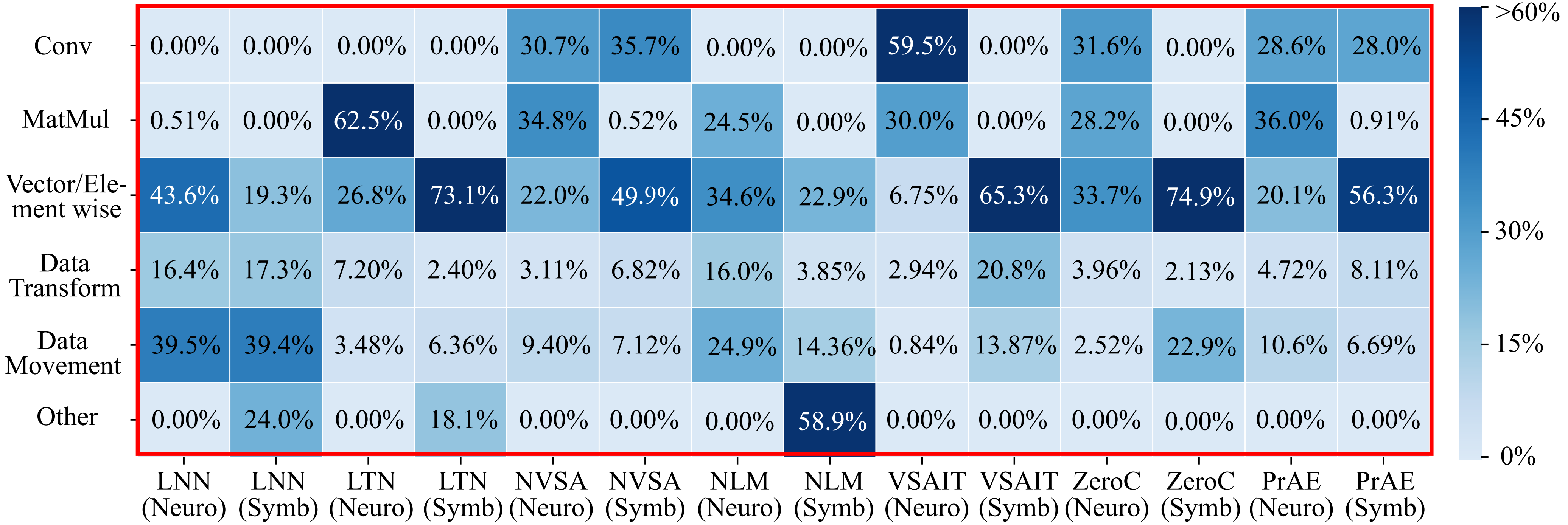

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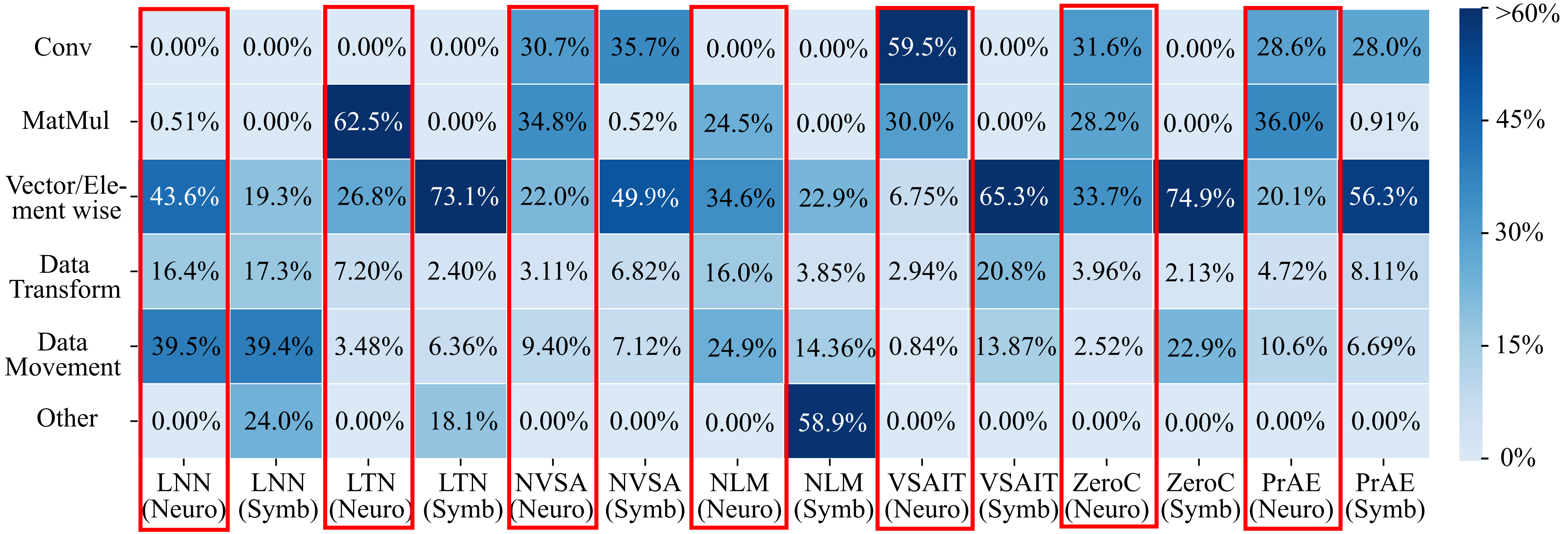

Neural dominated by MatMul and Conv operations;

Workload Characterization - Operator

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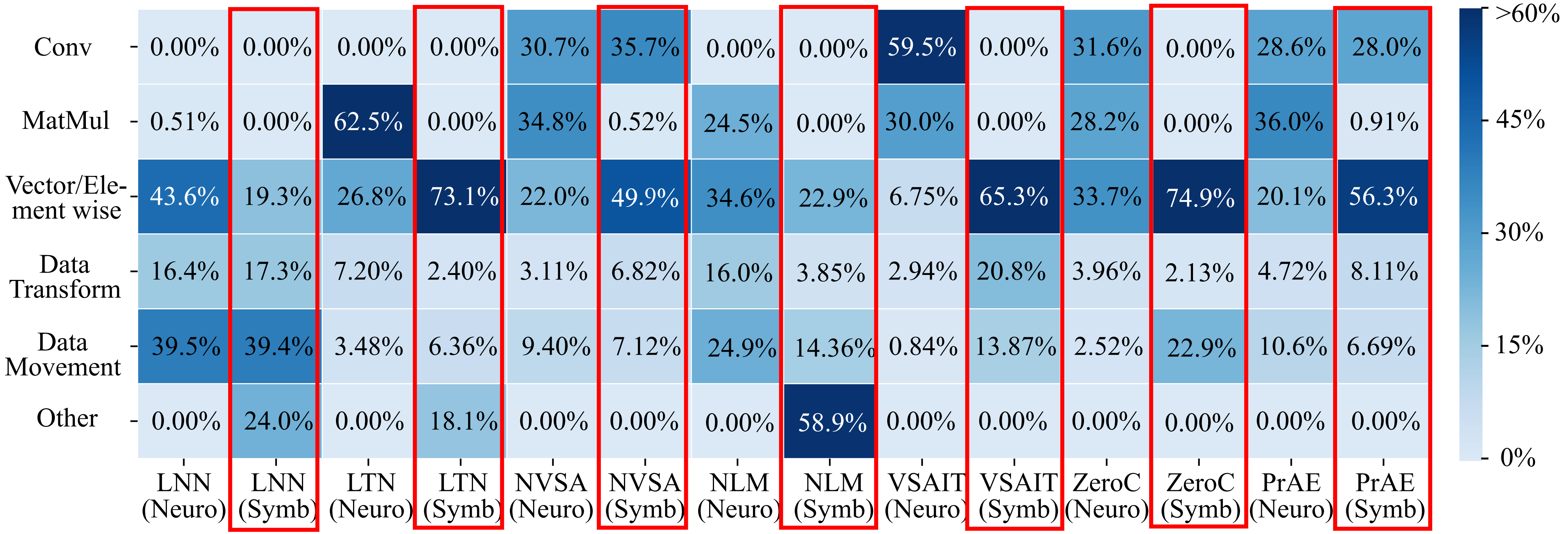
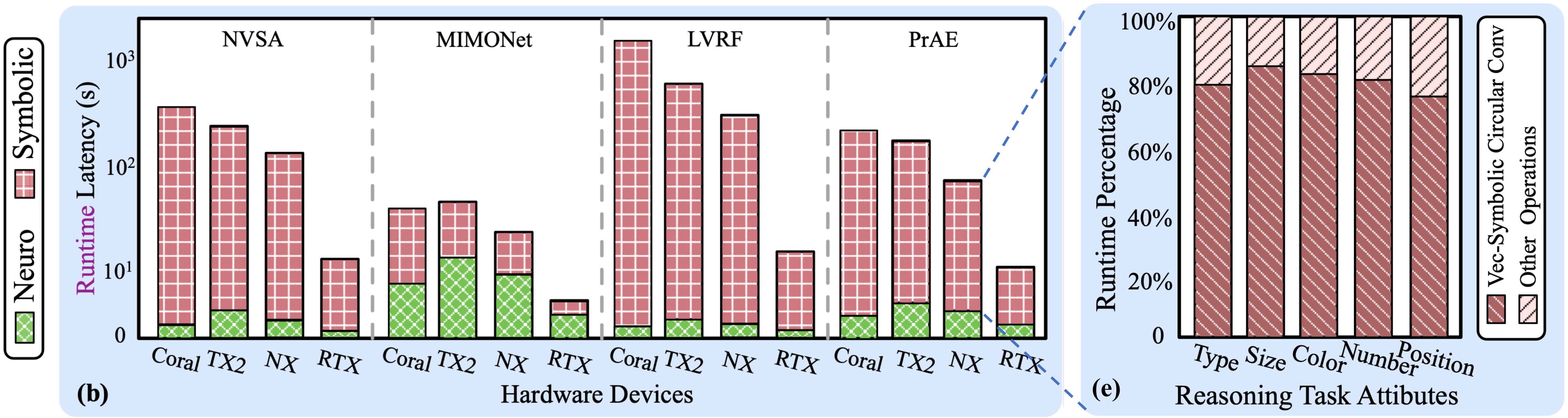


Neural dominated by MatMul and Conv operations; Symbolic dominated by vector/element-wise and logical operations

Workload Characterization - Operator



One example of dominated symbolic operation is **vector-symbolic circular convolutions**

Workload Characterization – Kernel Behavior

	Neuro Kernel		Symbolic Kernel	
	segmm_nn	relu_nn	vectorized	elementwise
Runtime Percentage (%)				
Compute Throughput (%)				
ALU Utilization (%)				
L1 Cache Hit Rate (%)				
L2 Cache Hit Rate (%)				
L1 Cache Throughput (%)				
L2 Cache Throughput (%)				
DRAM BW Utilization (%)				

Why system Inefficiency?

Workload Characterization – Kernel Behavior

	Neuro Kernel		Symbolic Kernel	
	segmm_nn	relu_nn	vectorized	elementwise
Runtime Percentage (%)	18.2	10.4	37.5	12.4
Compute Throughput (%)	**95.1**	**92.9**	3.0	2.3
ALU Utilization (%)	**90.1**	**48.3**	**5.9**	**4.5**
L1 Cache Hit Rate (%)				
L2 Cache Hit Rate (%)				
L1 Cache Throughput (%)				
L2 Cache Throughput (%)				
DRAM BW Utilization (%)				

Symbolic exhibits **low ALU utilization**,

Workload Characterization – Kernel Behavior

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L1 Cache Hit Rate (%)	1.6	**51.6**	**29.5**	**33.3**
L2 Cache Hit Rate (%)	**86.8**	**65.5**	**48.6**	**34.3**
L1 Cache Throughput (%)				
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Symbolic exhibits low ALU utilization, **low cache hit rate**,

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L1 Cache Throughput (%)	79.7	82.6	28.4	10.8
L2 Cache Throughput (%)	19.2	17.5	29.8	22.8
DRAM BW Utilization (%)	14.9	24.2	**90.9**	**78.4**

Symbolic exhibits low ALU utilization, low cache hit rate, **massive data transfer**, resulting in hardware underutilization and inefficiency

Workload Characterization – Kernel Behavior

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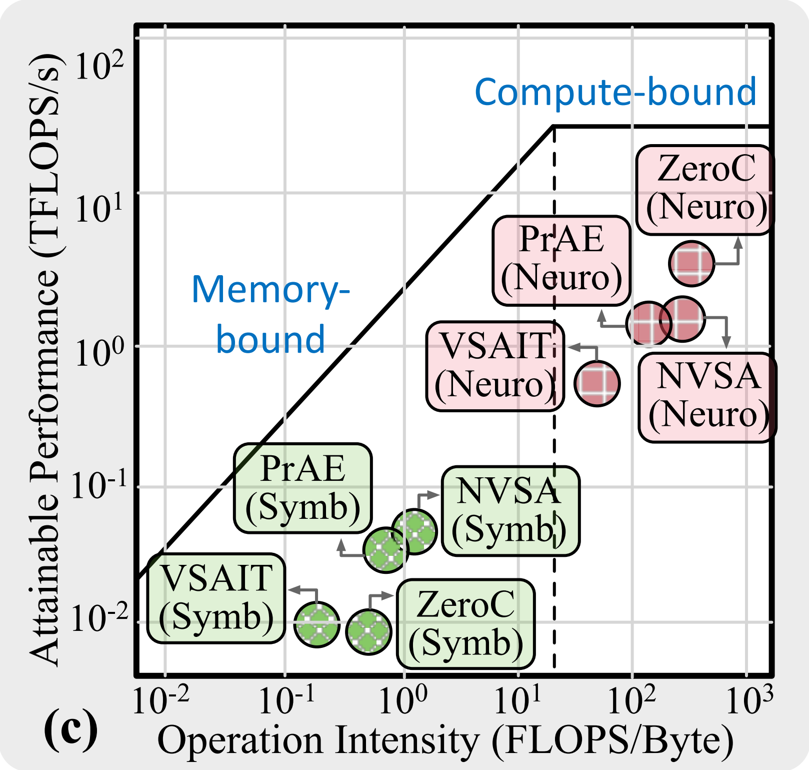
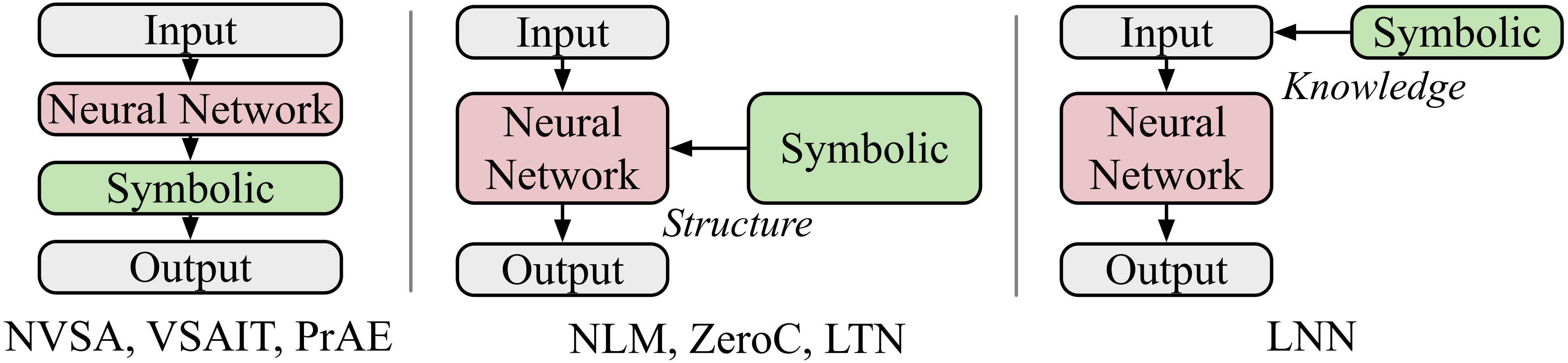


Neuro operations are **compute-bounded**, symbolic operations are **memory-bounded**.

Workload Characterization – Control Flow

- Data Dependence Graph analysis:



Neuro and symbolic components interaction requires **complex control flow**

Neural Network vs. Neuro-Symbolic

	Neural Network	Neuro-Symbolic

Neural Network vs. Neuro-Symbolic

	Neural Network	Neuro-Symbolic
Runtime	[Neural Network] < [Neural-Symbolic]	

Neural Network vs. Neuro-Symbolic

	Neural Network	Neuro-Symbolic
Runtime	[Neural Network] < [Neural-Symbolic]	
Compute Kernels	Neural kernels (Conv, MatMul, etc)	Heterogenous neural and symbolic kernels (vector, element, MatMul, graph, logic, etc)

Neural Network vs. Neuro-Symbolic

	Neural Network	Neuro-Symbolic
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Hardware Efficiency	Efficient on GPU/TPU	Inefficient on CPU/GPU/TPU (low ALU utilization, low L1 cache hit rate, high data movement, etc)

Neural Network vs. Neuro-Symbolic

	Neural Network	Neuro-Symbolic
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System Bound	Compute-bound / Memory-bound	Memory-bound

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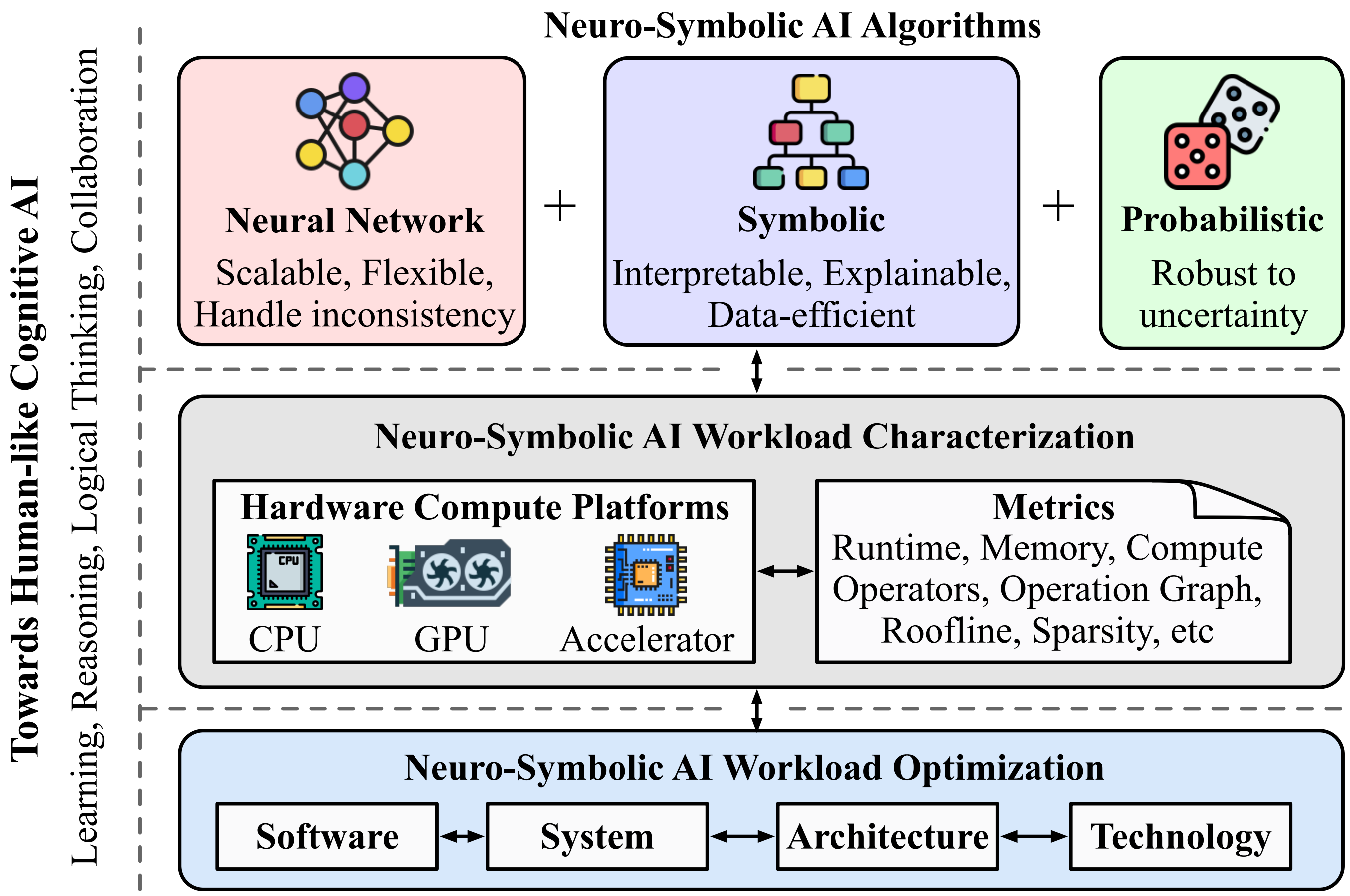
System Bound	Compute-bound / Memory-bound	Memory-bound
Dataflow	Simple flow control, High parallelism	Complex flow control, Low parallelism

This talk: Demystify Neuro-Symbolic AI for SW/HW Co-Design

<u>Characterize</u> Neuro-Symbolic Workloads

<u>Identify</u> Potential Inefficiency Reasons

<u>Optimize</u> Neuro-Symbolic Systems via Co-Design



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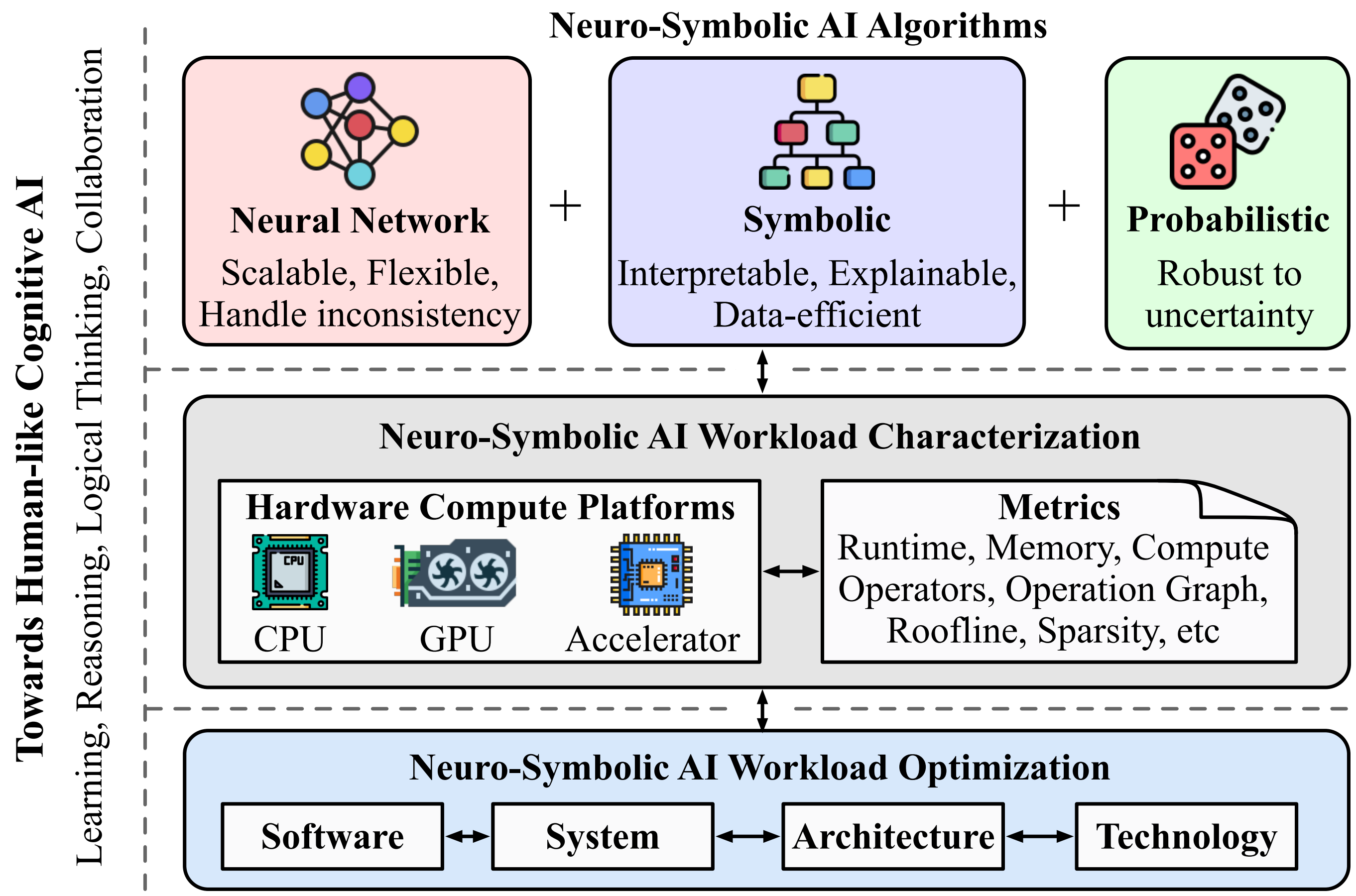
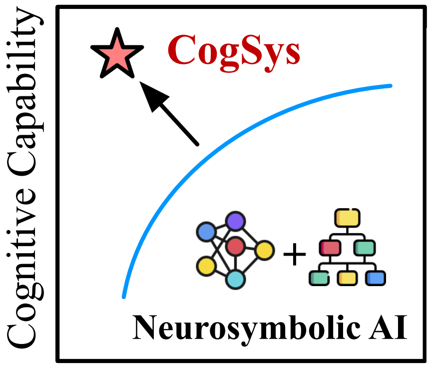


Zishen Wan*, Hanchen Yang*, Ritik Raj*, Che-Kai Liu, Ananda Samajdar, Arijit Raychowdhury, Tushar Krishna, **"CogSys: Efficient and Scalable Neurosymbolic Cognition System via Algorithm-Hardware Co-Design"**, *in* ***HPCA 2025***

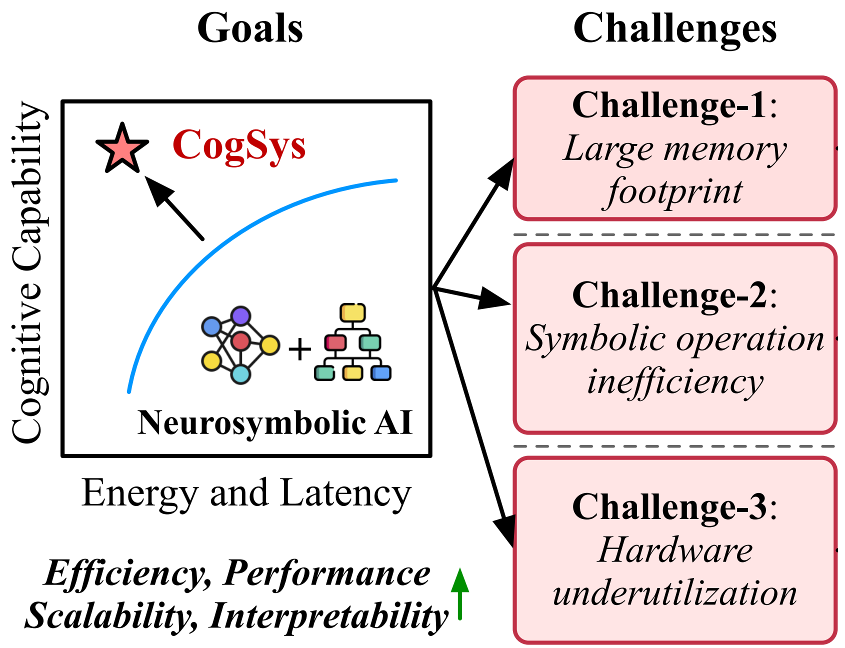
CogSys: Co-Design for Neuro-Symbolic AI

Goals



Efficiency, Performance
Scalability, Interpretability ↑

CogSys: Co-Design for Neuro-Symbolic AI



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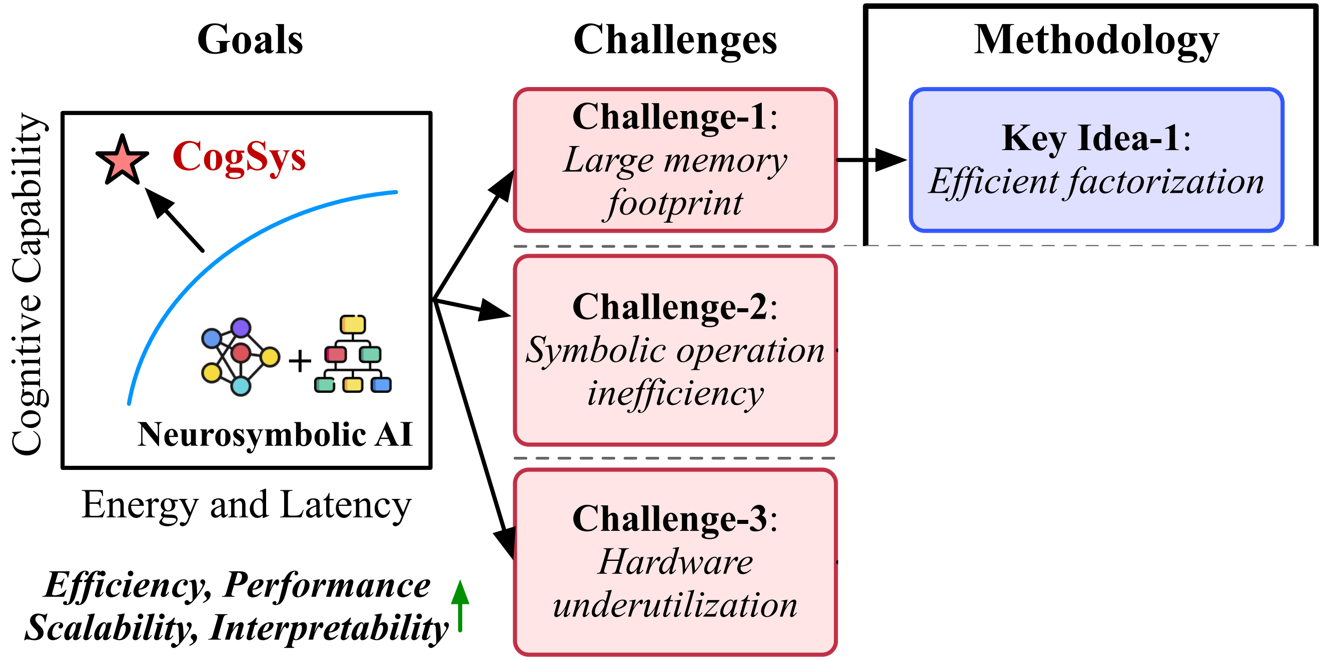

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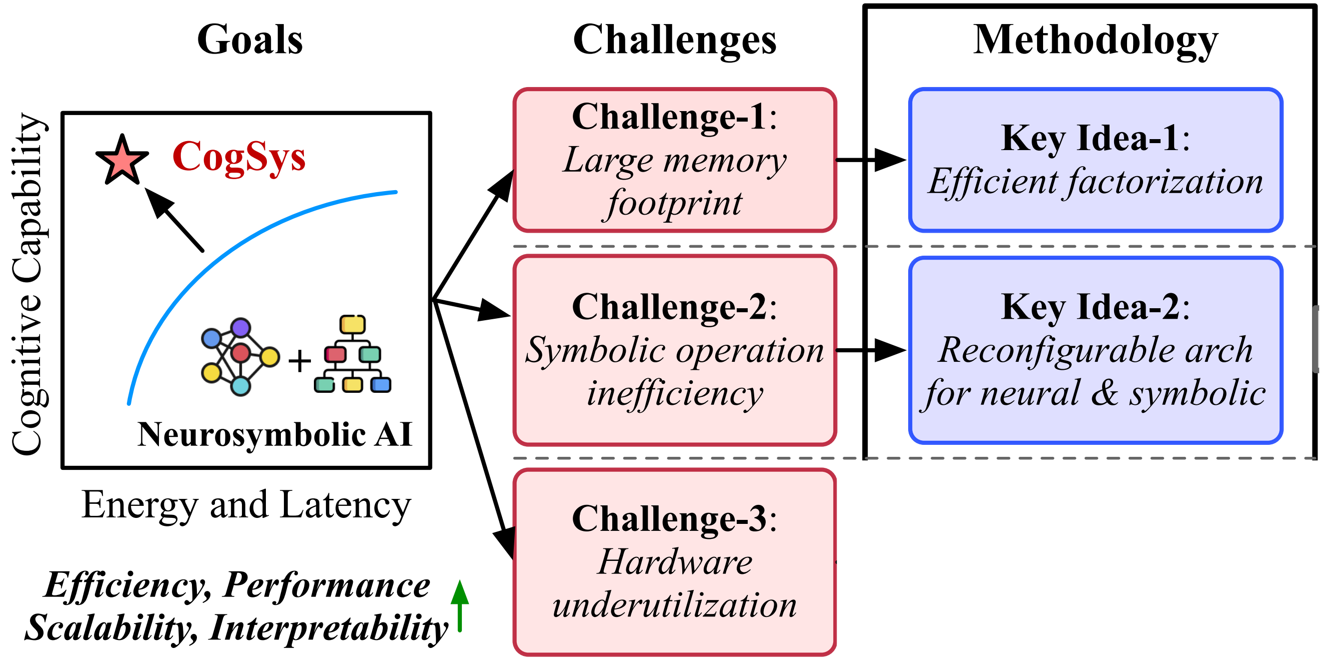

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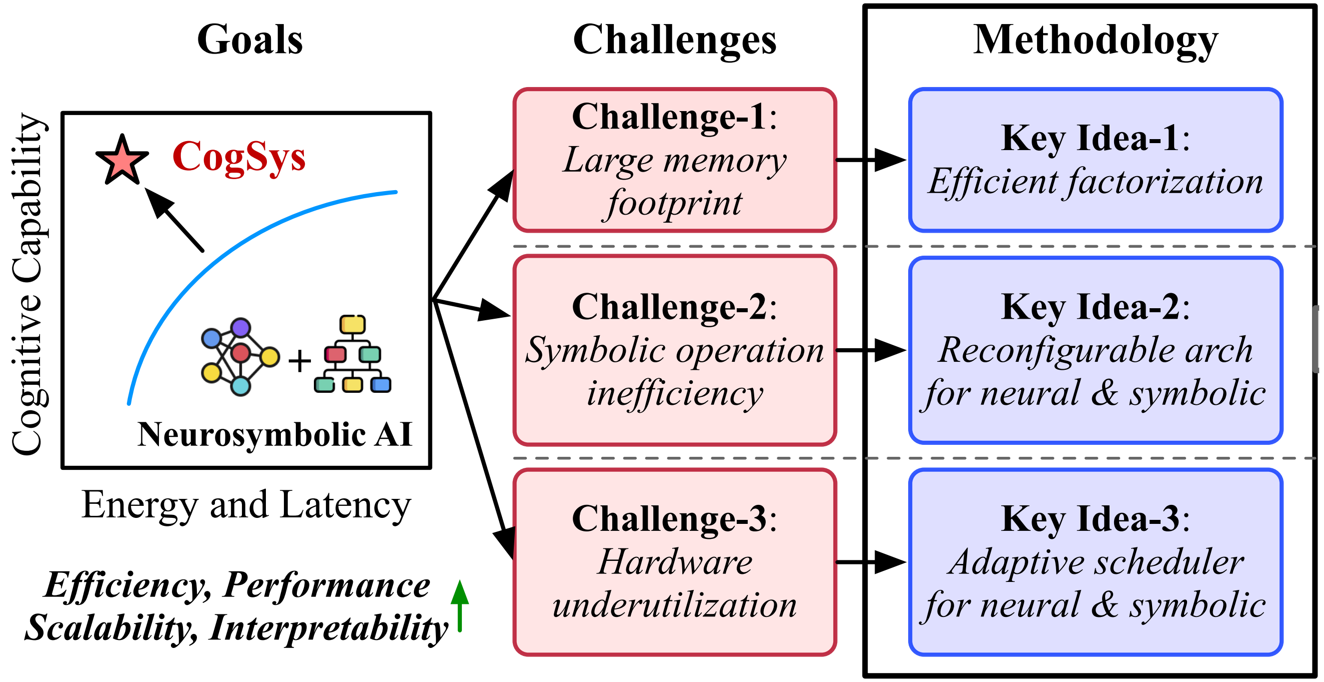

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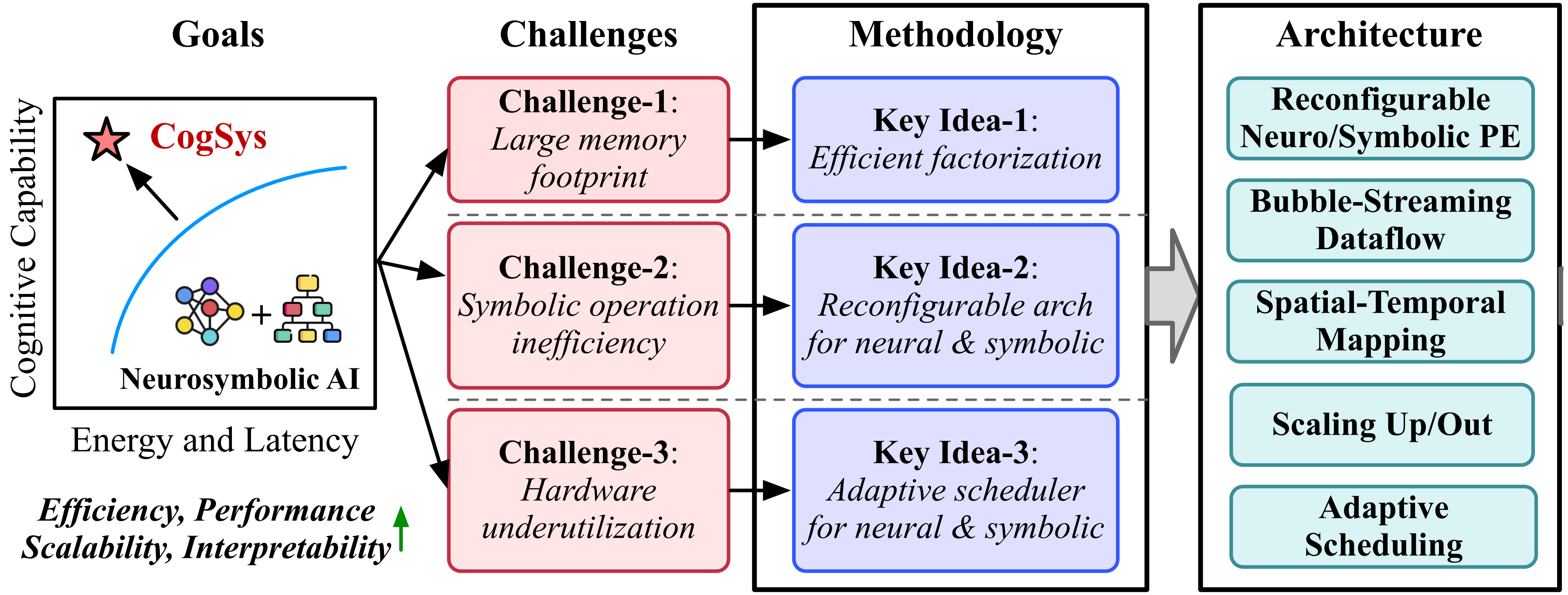

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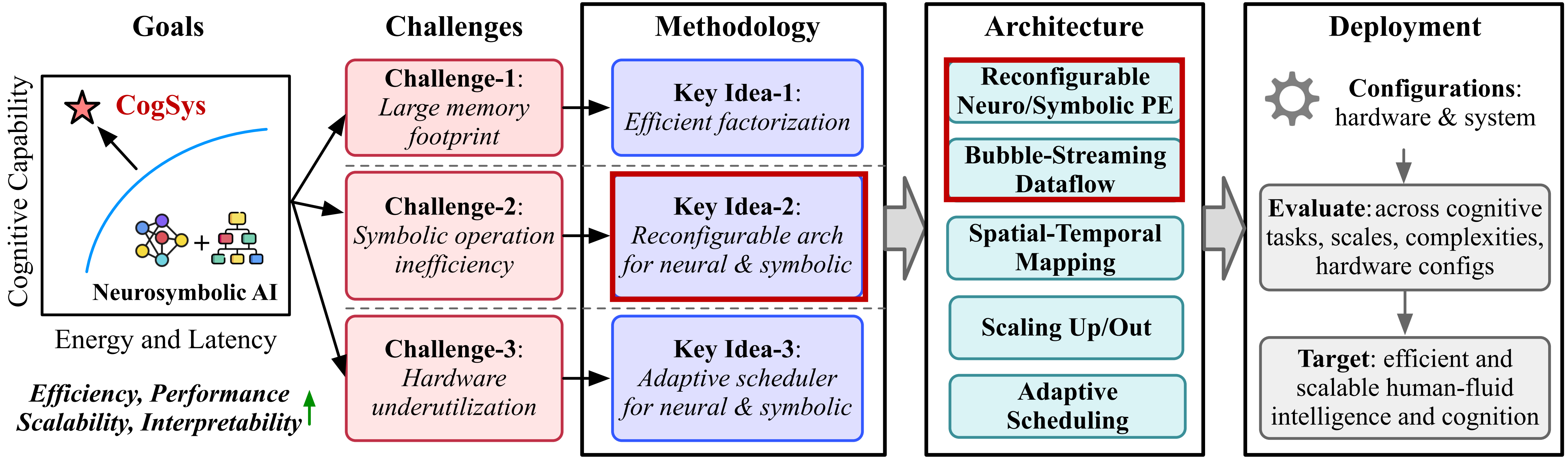
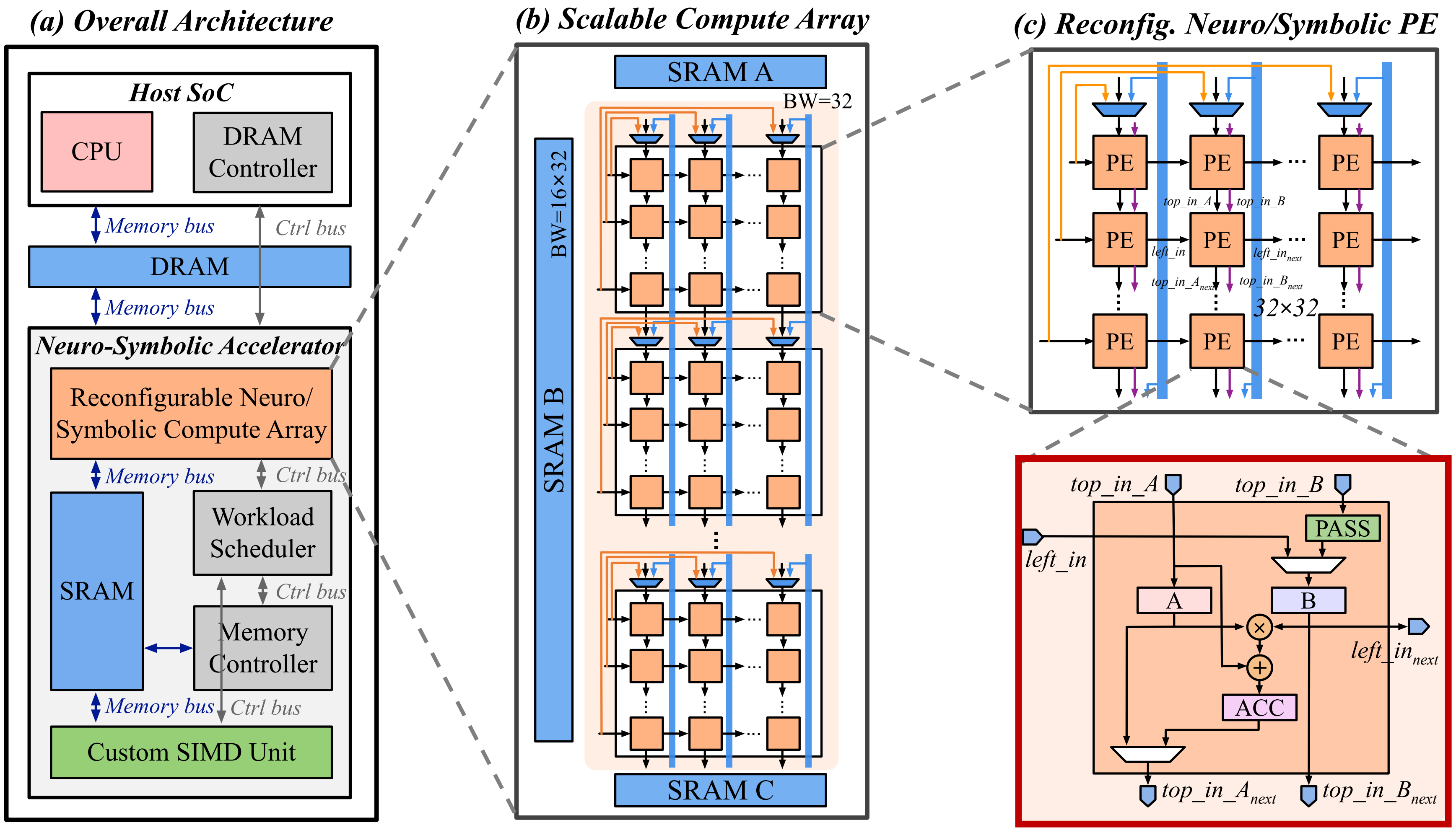
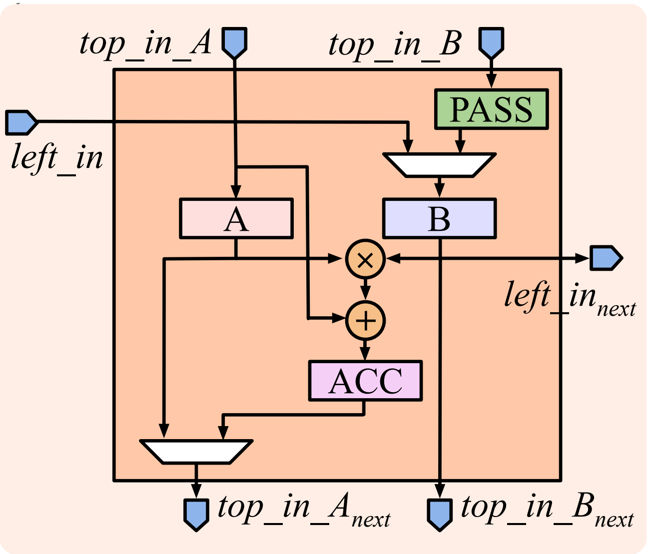


Hardware Architecture Overview



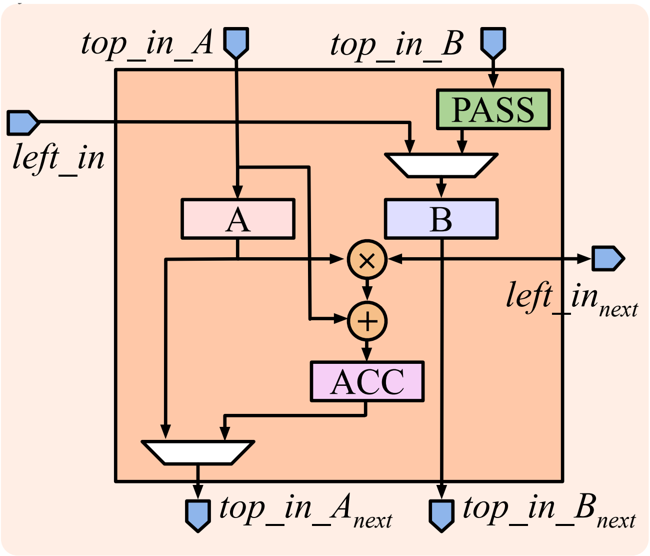
Reconfigurable Neuro/Symbolic PE



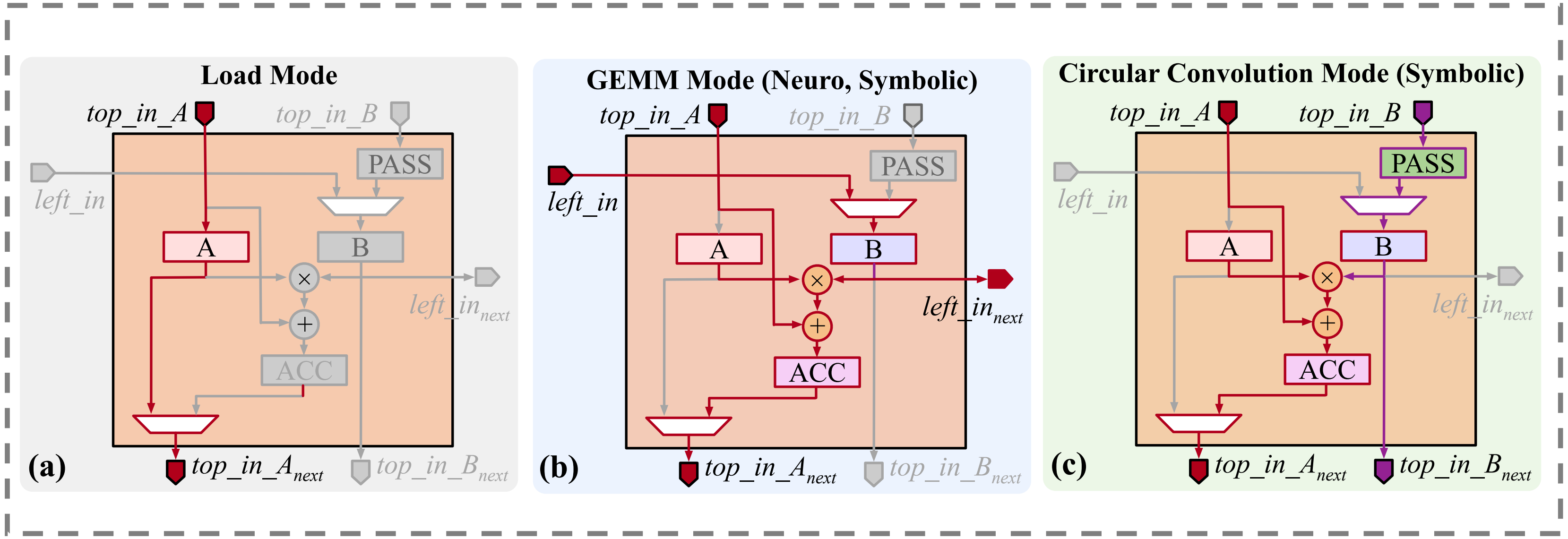
Micro-architecture of
reconfigurable neuro/symbolic PE

Reconfigurable neuro/symbolic PE incurs **low area overhead** based on systolic array PE;

Reconfigurable Neuro/Symbolic PE



Micro-architecture of reconfigurable neuro/symbolic PE

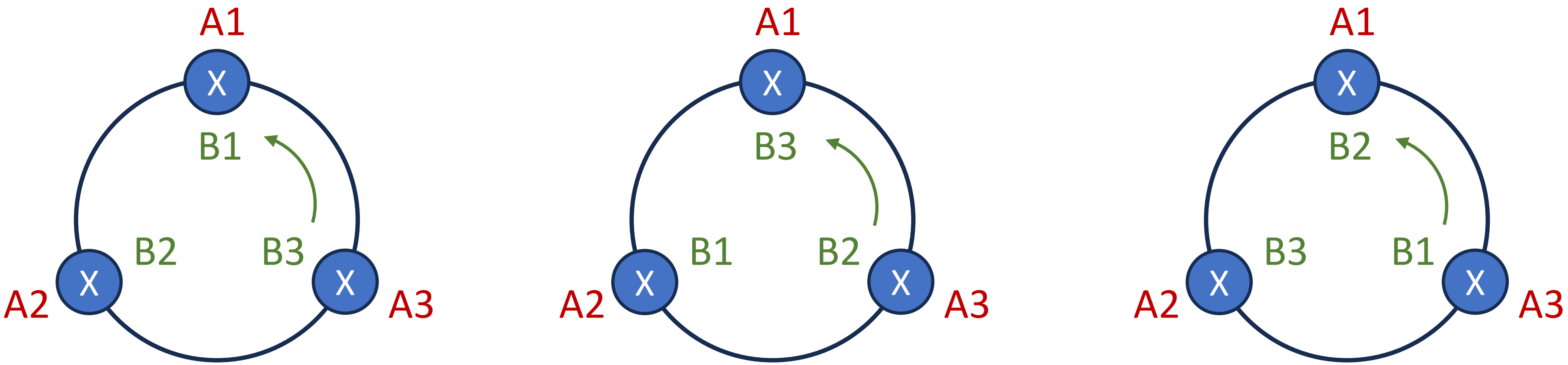


Operation mode of reconfigurable neuro/symbolic PE

Reconfigurable neuro/symbolic PE incurs **low area overhead** based on systolic array PE; The PE is reconfigurable for **three operation modes**: load, neuro, symbolic

What is Circular Convolution?

$$\begin{bmatrix} A1 \\ A2 \\ A3 \end{bmatrix} \odot \begin{bmatrix} B1 \\ B2 \\ B3 \end{bmatrix} = \begin{pmatrix} A1B1+A2B2+A3B3 \\ A1B3+A2B1+A3B2 \\ A1B2+A2B3+A2B1 \end{pmatrix}$$



A1B1+A2B2+A3B3 | A1B3+A2B1+A3B2 | A1B2+A2B3+A2B1

Bubble Streaming Dataflow

Vector-Symbolic Circular Convolution Example (3 CircConv):

CircConv #1: (A1, A2, A3) ⊙ (B1, B2, B3)

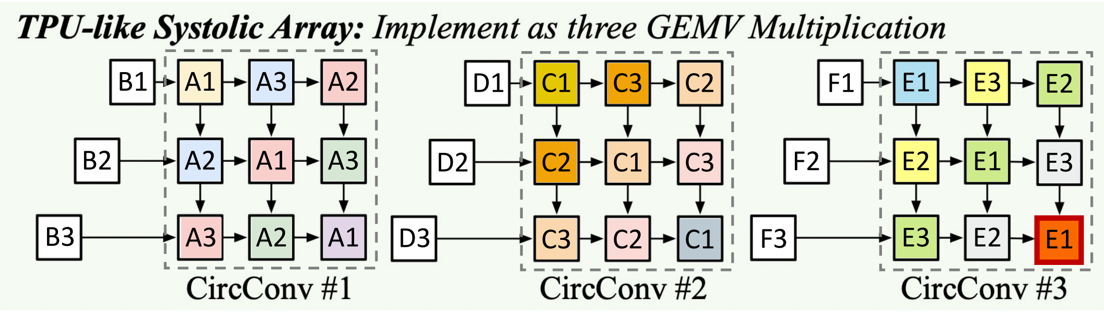
CircConv #2: (C1, C2, C3) ⊙ (D1, D2, D3)

CircConv #3: (E1, E2, E3) ⊙ (F1, F2, F3)

CircConv #1 Computation:

(A1, A2, A3) ⊙ (B1, B2, B3) =

(A1B1+A2B2+A3B3, A1B3+A2B1+A3B2, A1B2+A2B3+A2B1)



Cycles:

TPU: Finish at (3n+15) = 24 cycles

For symbolic operation:

- TPU-like array **suffers from** low parallelism & high memory access;

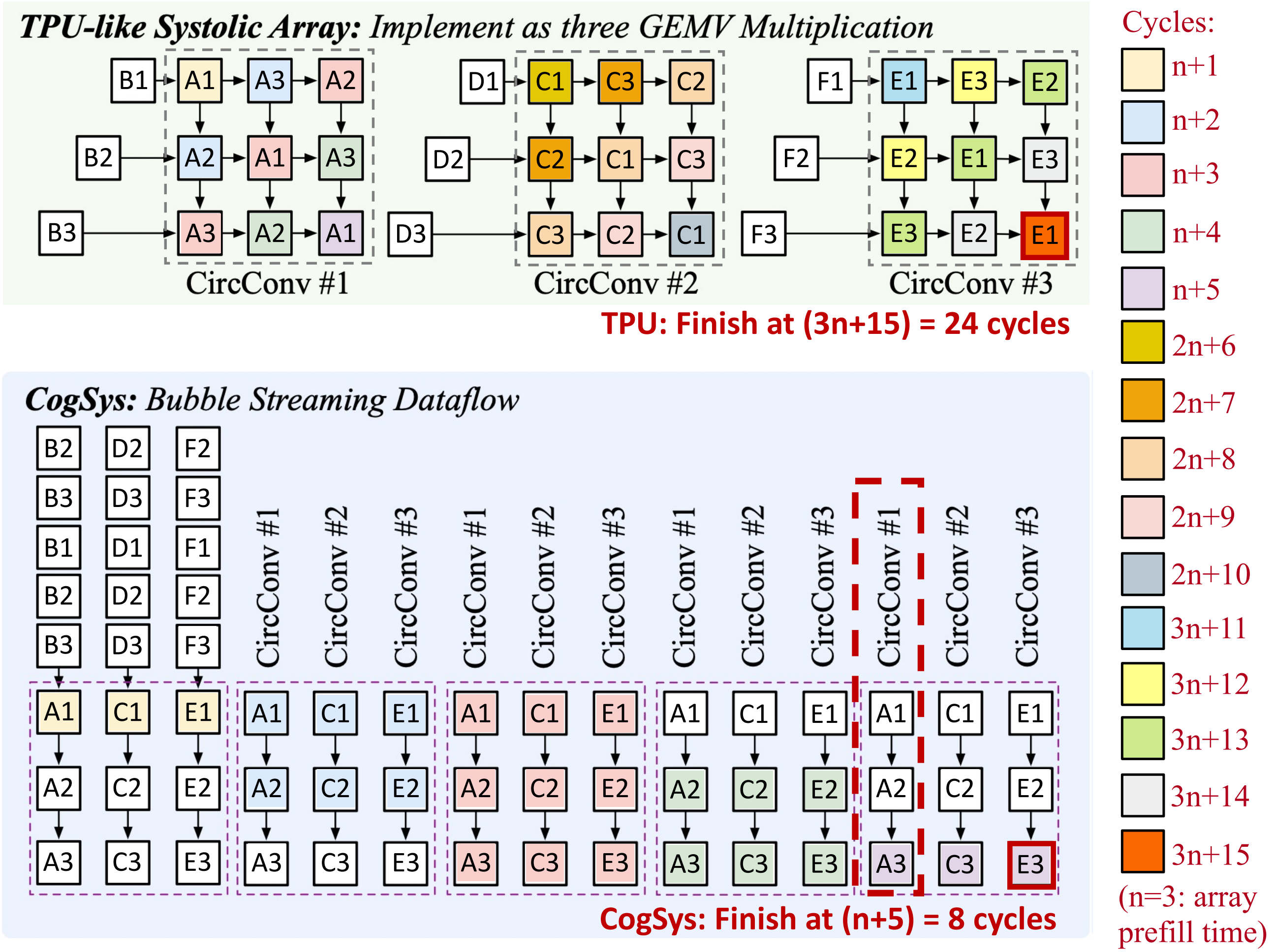
Bubble Streaming Dataflow

Vector-Symbolic Circular Convolution Example (3 CircConv):
CircConv #1: (A1, A2, A3)⊙(B1, B2, B3)
CircConv #2: (C1, C2, C3)⊙(D1, D2, D3)
CircConv #3: (E1, E2, E3) ⊙(F1, F2, F3)

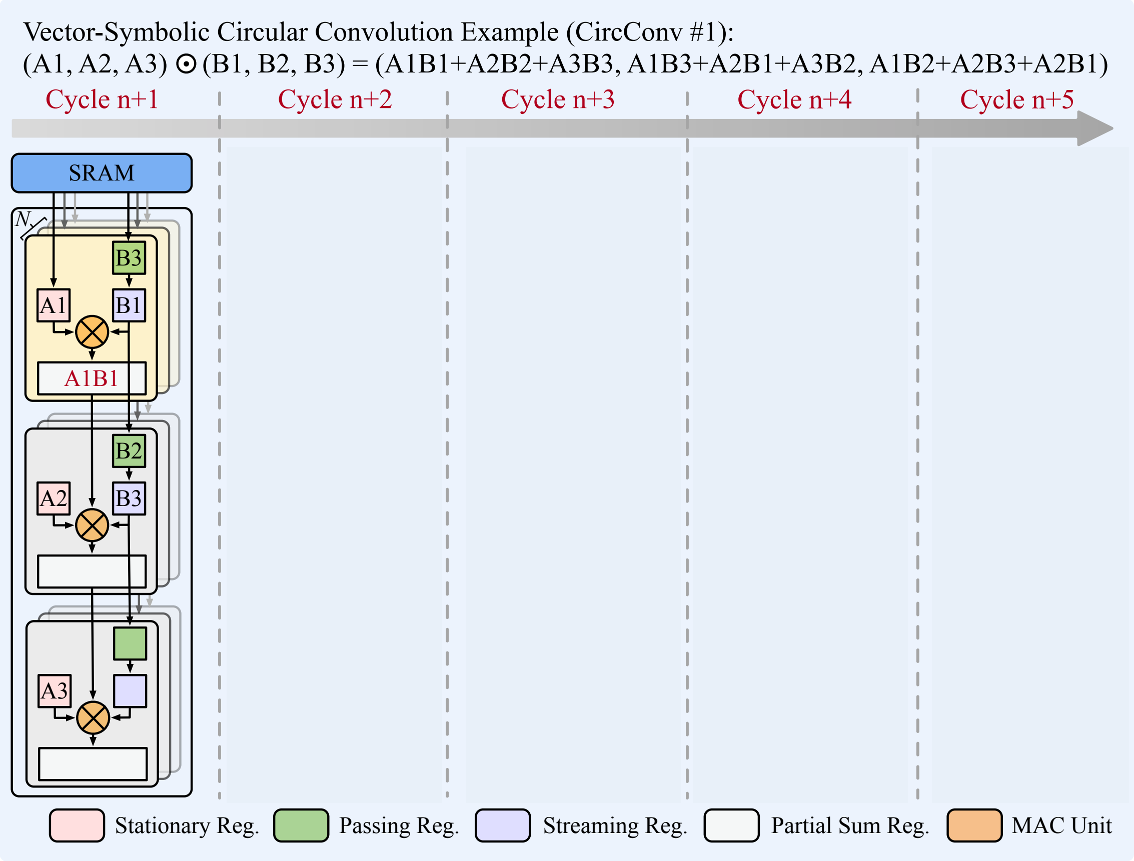
CircConv #1 Computation:
(A1, A2, A3) ⊙ (B1, B2, B3) =
(A1B1+A2B2+A3B3, A1B3+A2B1+A3B2, A1B2+A2B3+A2B1)

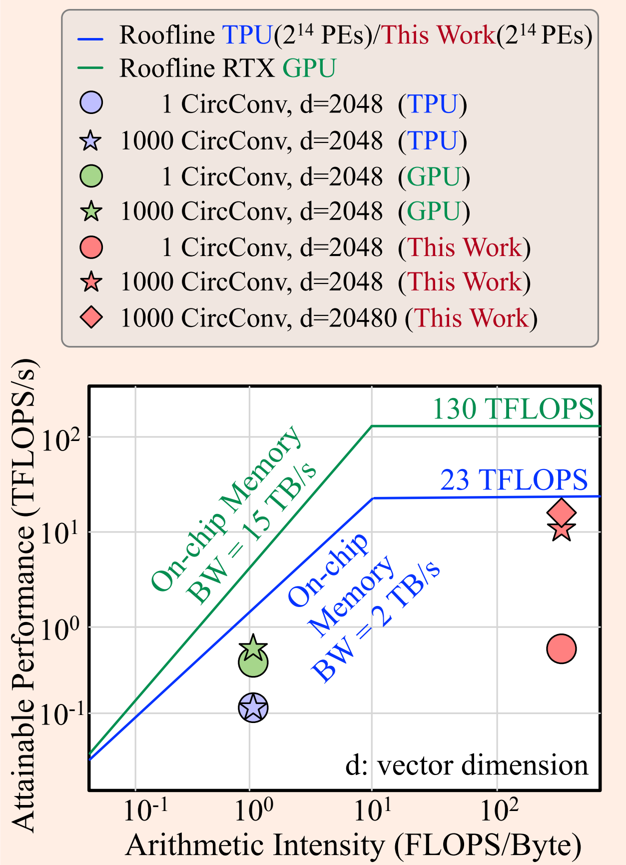
For symbolic operation:

- TPU-like array **suffers from** low parallelism & high memory access;
- Bubble streaming dataflow **improve parallelism, arithmetic intensity, and data reuse.**



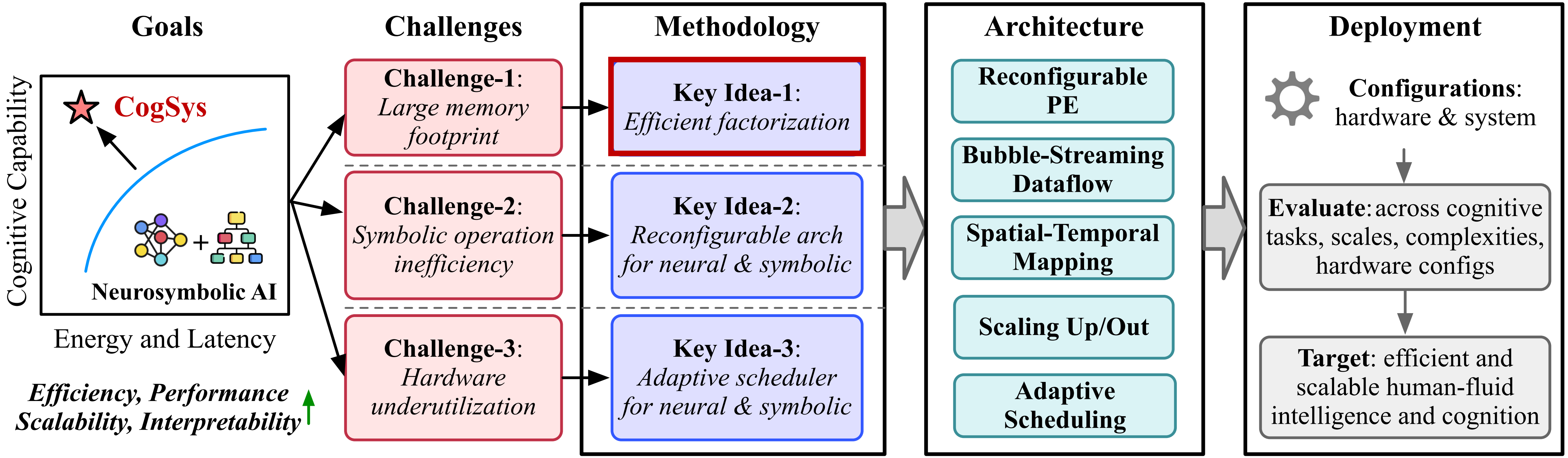
Bubble Streaming Dataflow



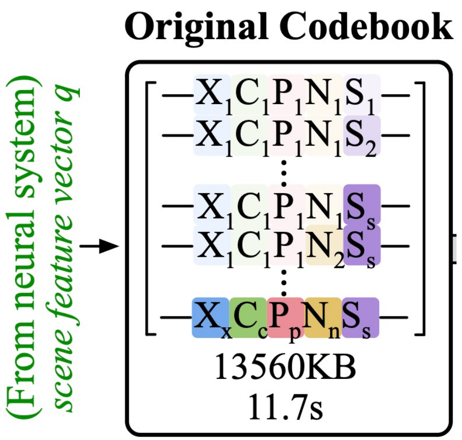


Bubble streaming dataflow flow improve parallelism, arithmetic intensity, and data reuse

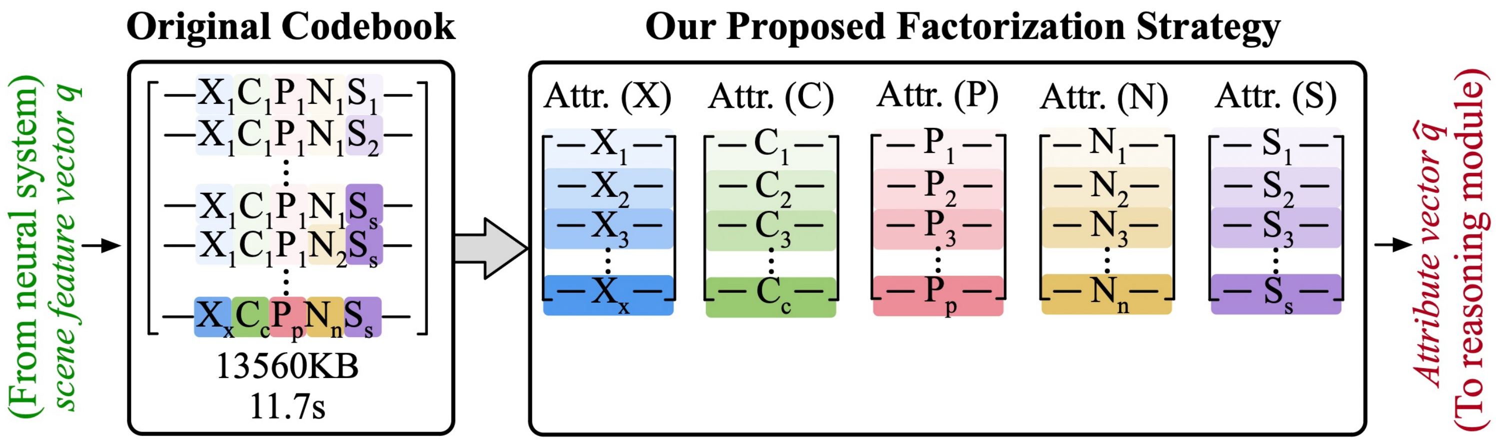
CogSys: Co-Design for Neuro-Symbolic AI



Algorithm Optimization – Efficient Factorization

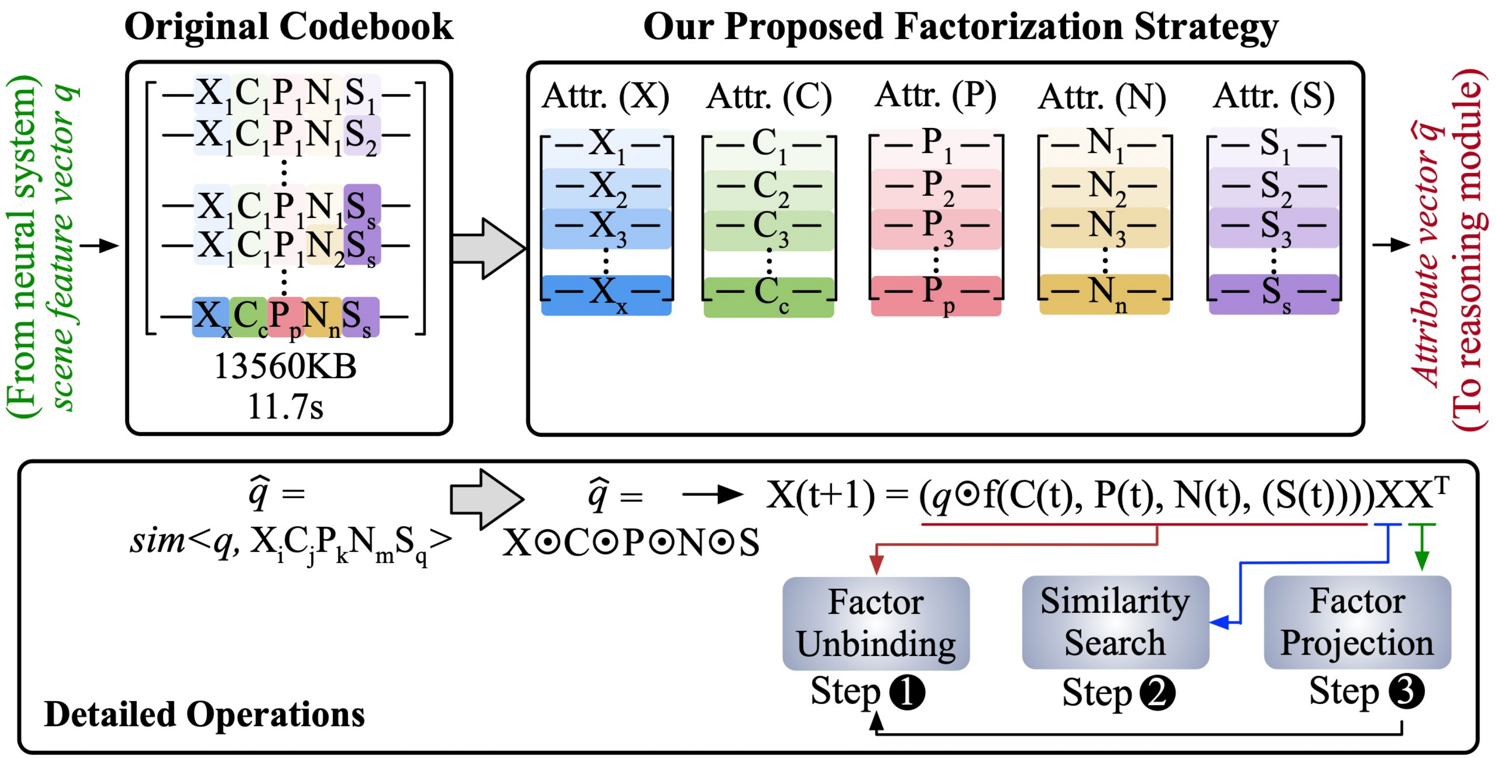


Algorithm Optimization – Efficient Factorization



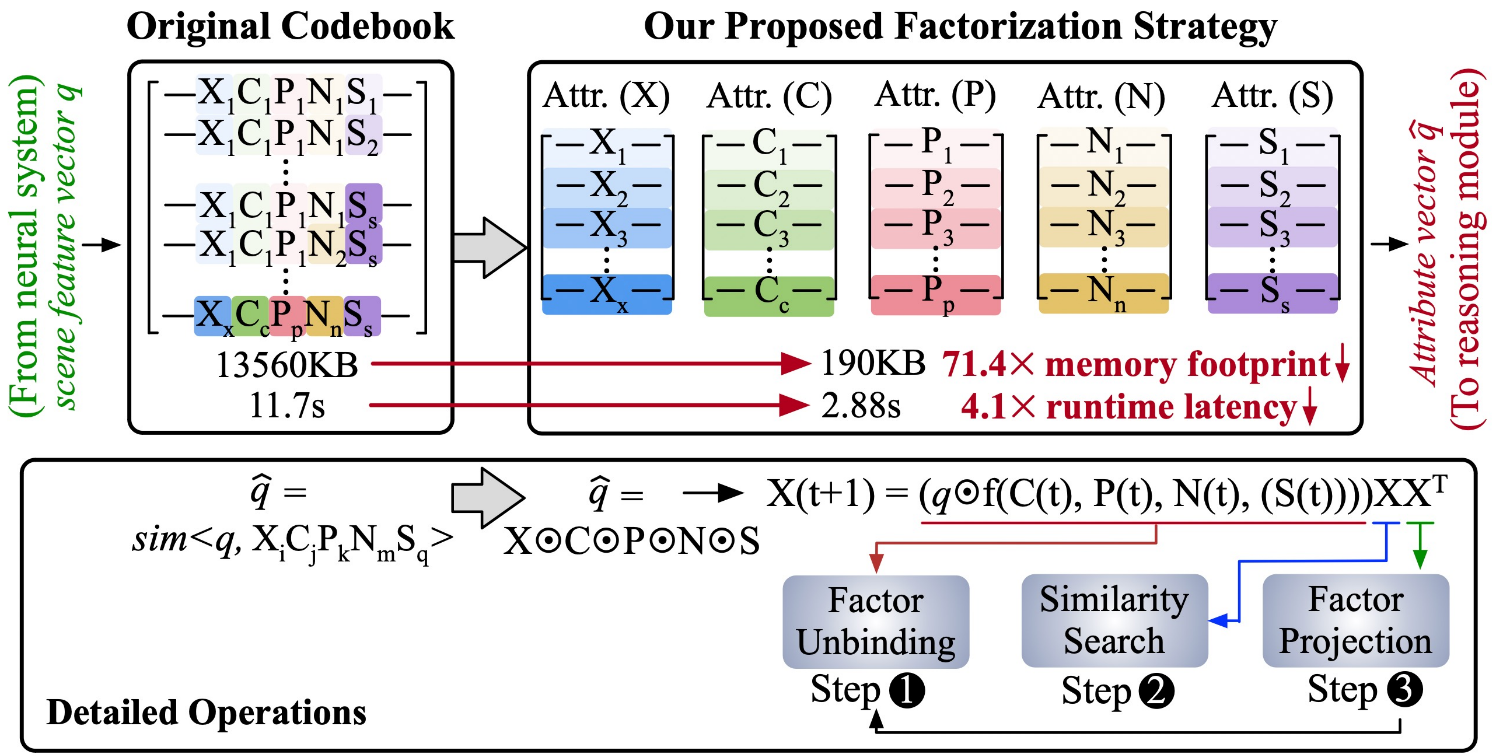
Factorization **disentangles** large symbolic knowledge codebook into small volume of attributes

Algorithm Optimization – Efficient Factorization



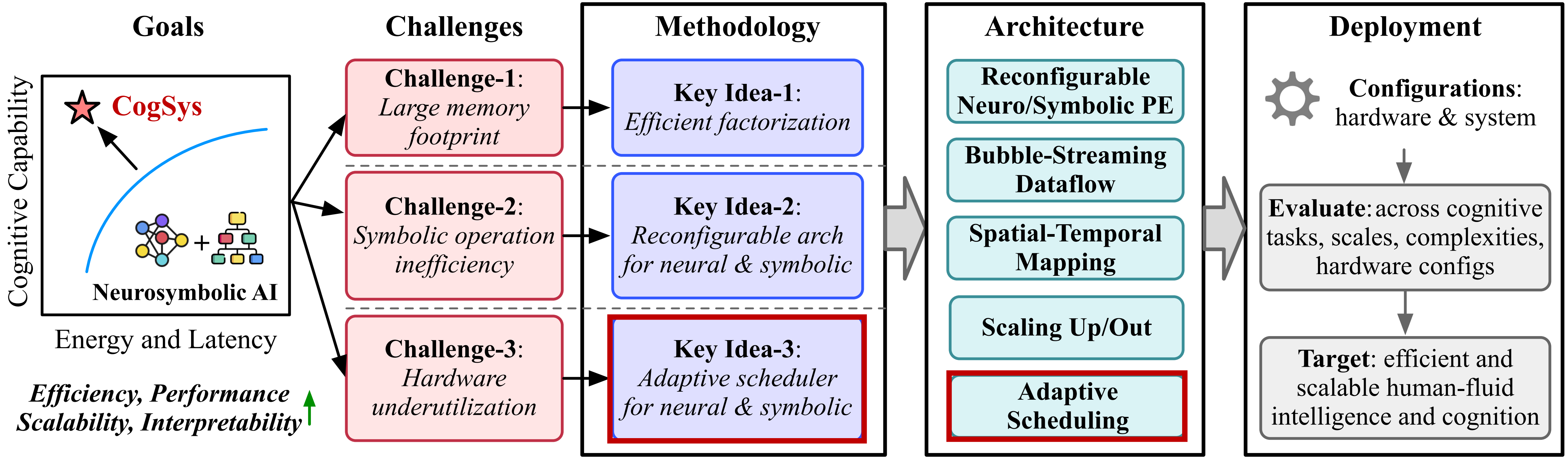
Factorization **disentangles** large symbolic knowledge codebook into small volume of attributes

Algorithm Optimization – Efficient Factorization

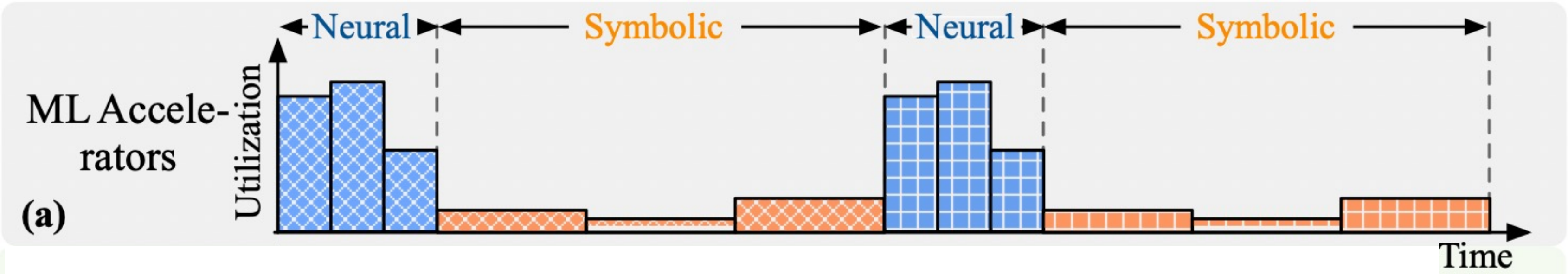


Factorization **disentangles** large symbolic knowledge codebook into small volume of attributes, thus **reducing computational time and space complexity**

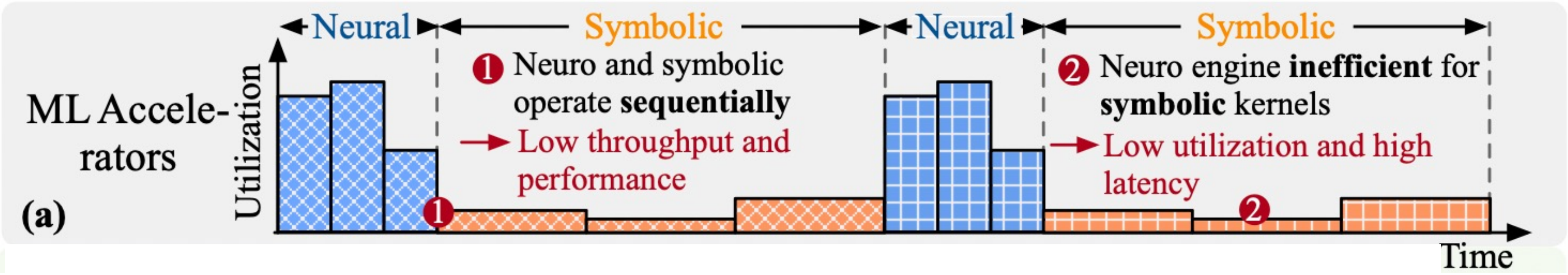
CogSys: Co-Design for Neuro-Symbolic AI



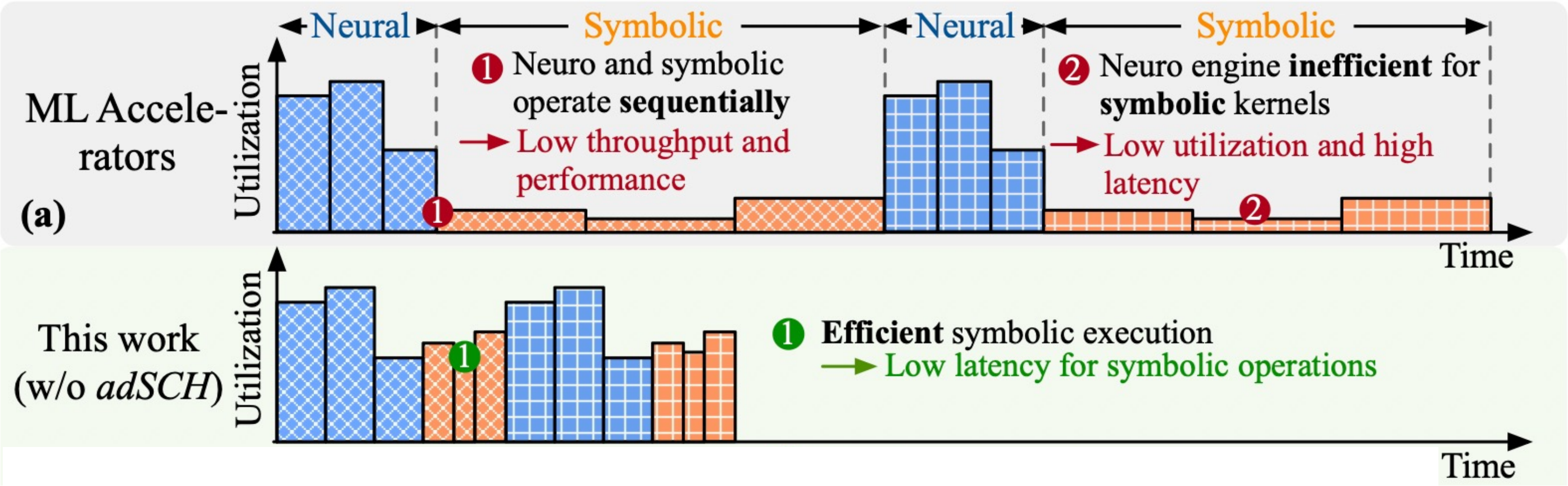
System Optimization - Adaptive Scheduling



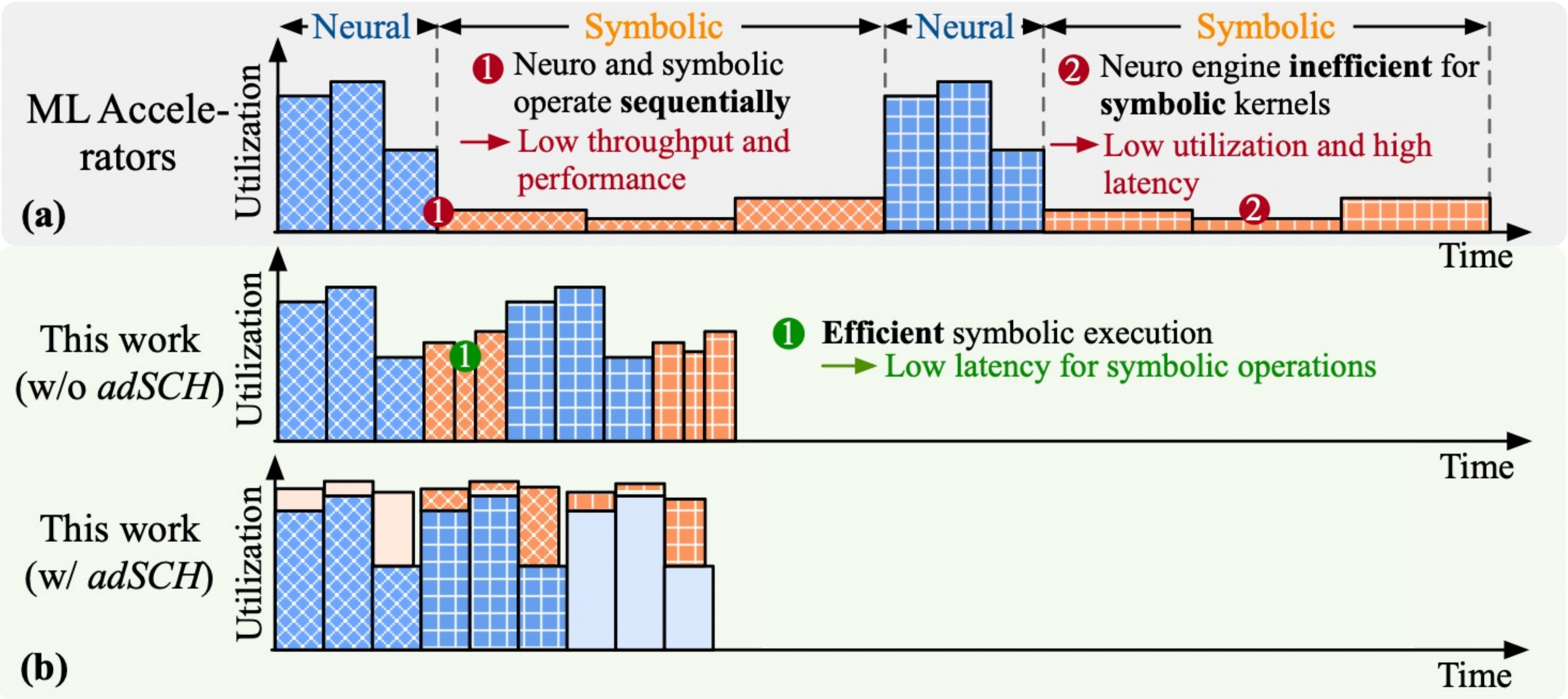
System Optimization - Adaptive Scheduling



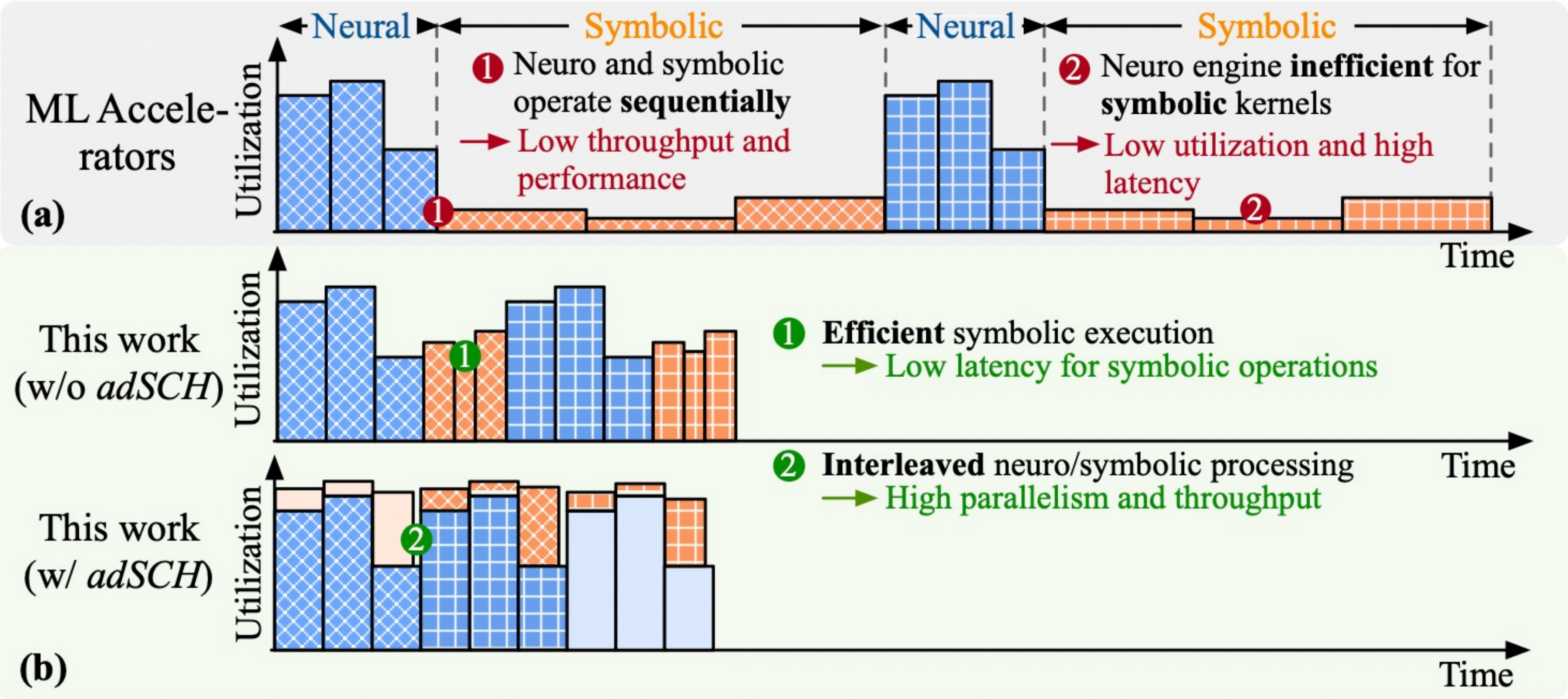
System Optimization - Adaptive Scheduling



System Optimization - Adaptive Scheduling

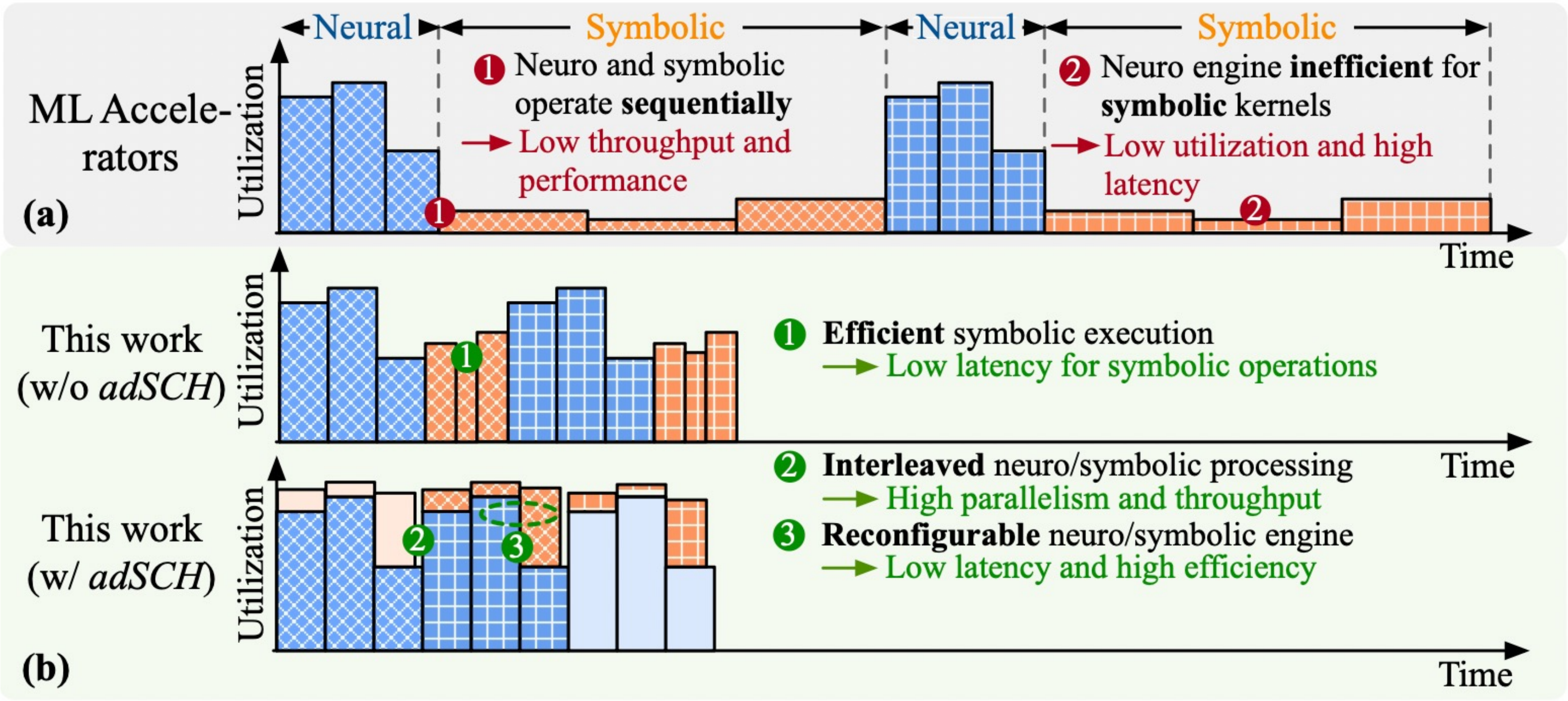


System Optimization - Adaptive Scheduling



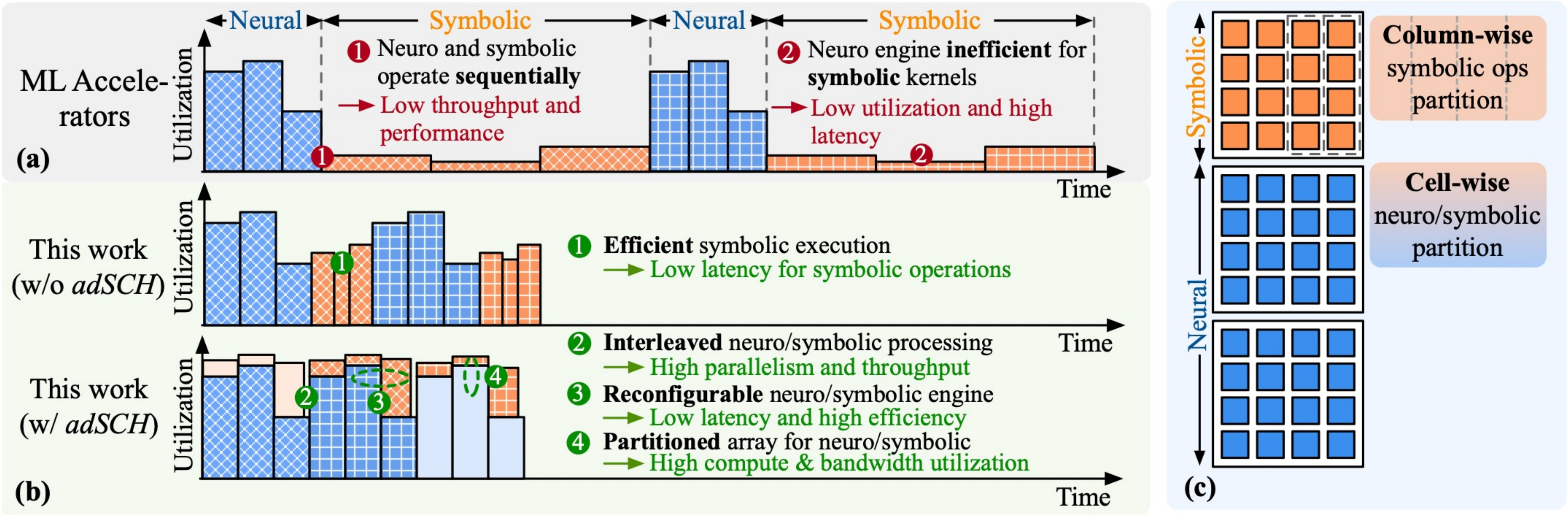
Adaptive scheduling enables **interleaved**

System Optimization - Adaptive Scheduling



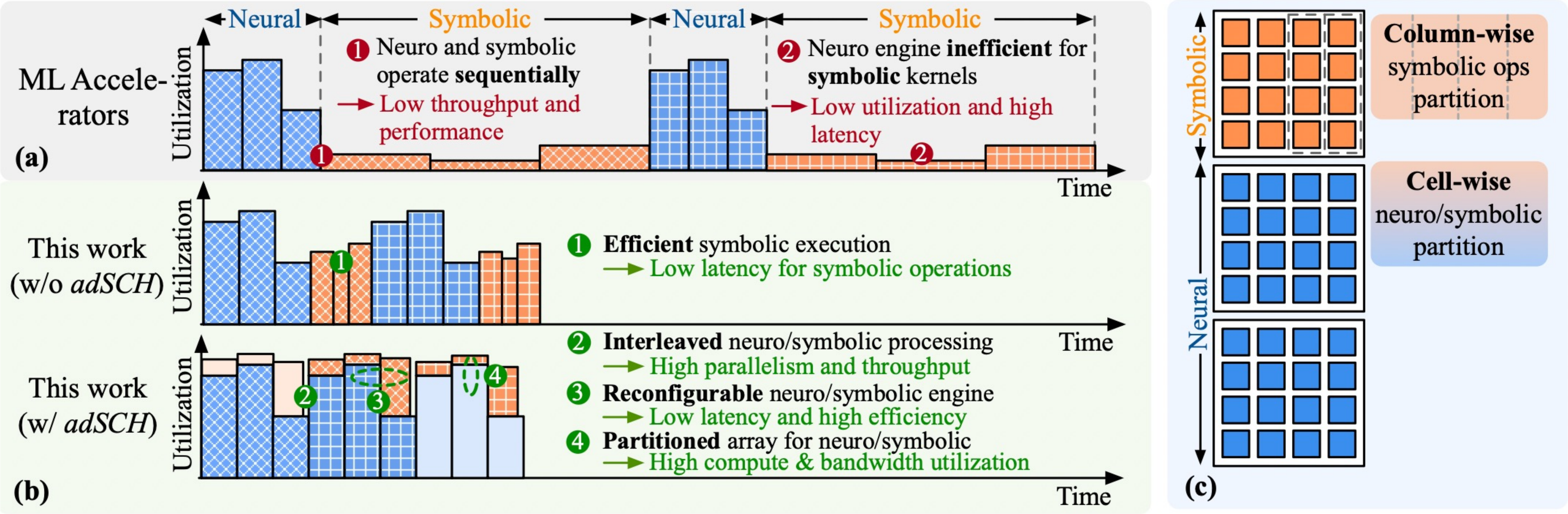
Adaptive scheduling enables **interleaved** and **reconfigurable** neuro/symbolic processing

System Optimization - Adaptive Scheduling



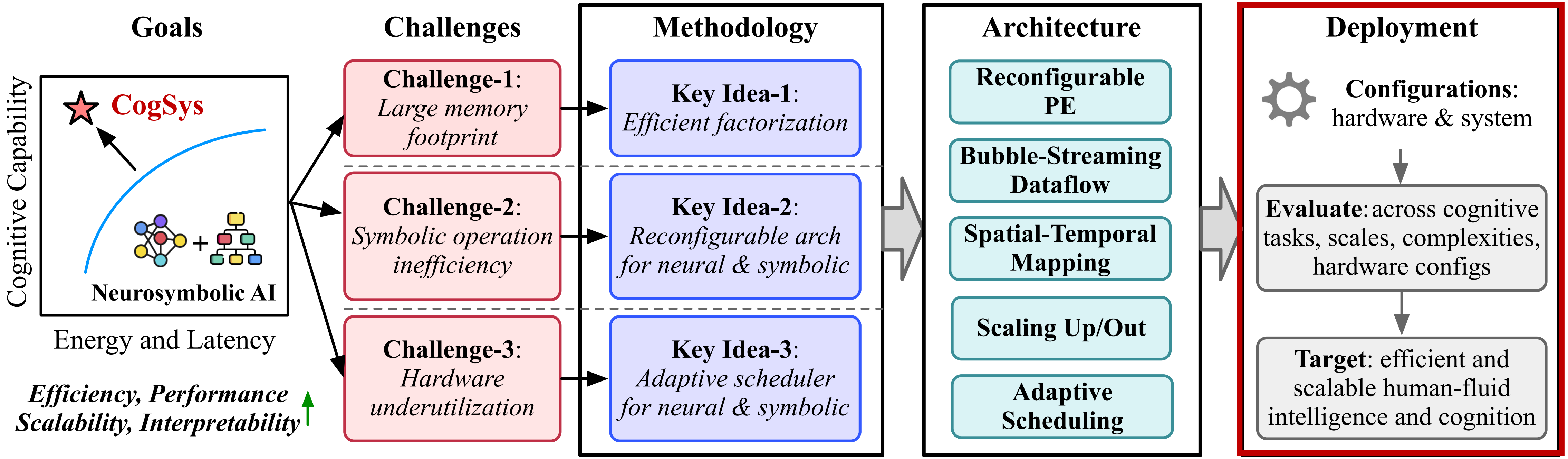
Adaptive scheduling enables **interleaved** and **reconfigurable** neuro/symbolic processing with **partitioned array**

System Optimization - Adaptive Scheduling



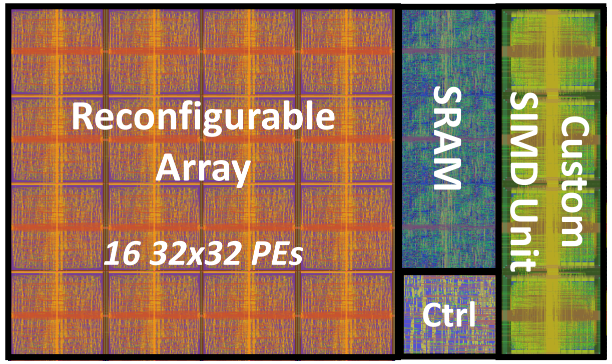
Adaptive scheduling enables **interleaved** and **reconfigurable** neuro/symbolic processing with **partitioned array**, improving parallelism, latency, efficiency, and utilization

CogSys: Co-Design for Neuro-Symbolic AI



Evaluation – Setup and Accelerator Layout

Layout of Neuro-Symbolic Accelerator



Accelerator Specs

Technology	28 nm	Frequency	600 MHz
#Arrays	16	Voltage	1 V
Size of Each Array	32x32	Power	1.48 W
SRAM	4.5 MB	Area	4.9 mm^2

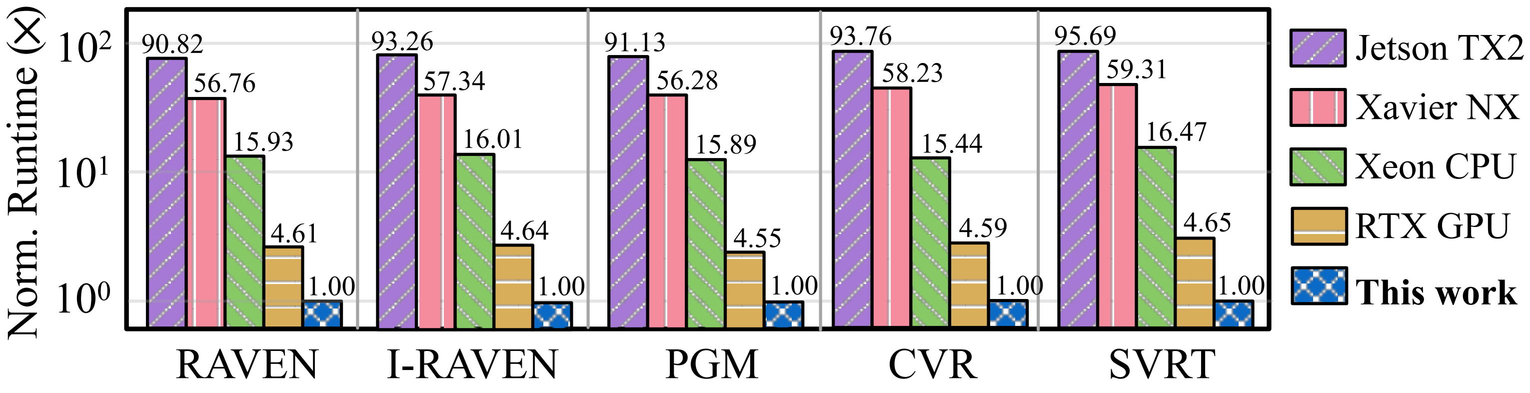
- **Task**: Cognitive reasoning tasks
- **Reasoning datasets**:
  - RAVEN, I-RAVEN, PGM, CVR, SVRT
- **Neuro-symbolic workloads**:
  - NVSA, MIMONet, LVRF
- **Hardware baseline**:
  - Jetson TX2, Xavier NX, RTX GPU, Xeon CPU
  - ML accelerators (TPU, MTIA, Gemmini)

Evaluation – Algorithm Performance

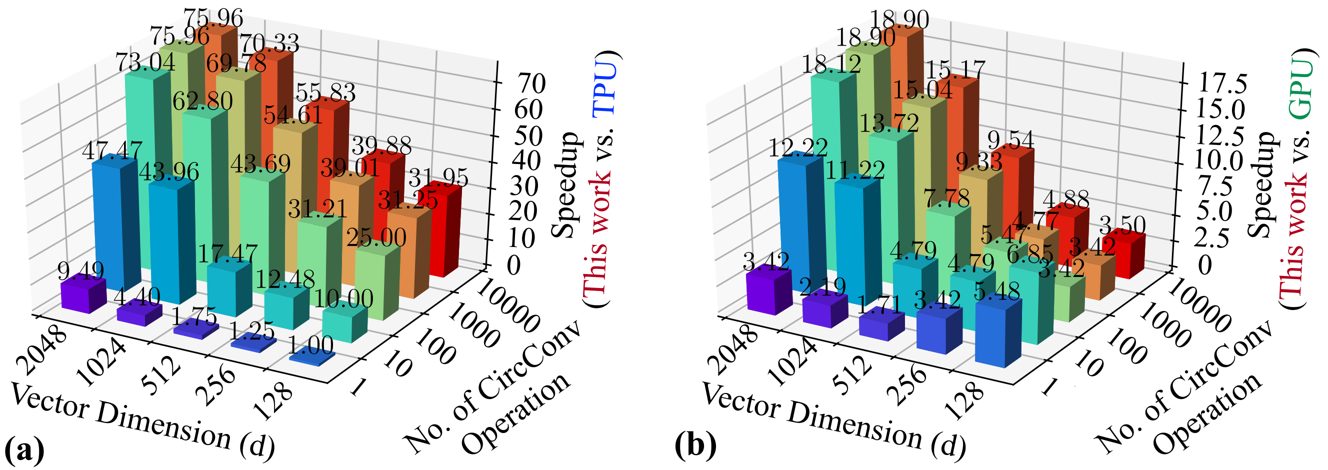
Dataset Accuracy	Neurosymbolic Model			Non-neurosymbolic		Human
	NVSA	**Our Design (+Algo Opt.)**	**Our Design (+Quant.)**	ResNet18	GPT-4	
RAVEN	98.5%	98.9%	98.7%	53.4%	89.0%	84.4%
I-RAVEN	99.0%	99.0%	98.8%	40.3%	86.0%	78.6%
PGM	68.3%	68.7%	68.4%	36.8%	56.0%	N/A
#Parameters	38 MB	32 MB	8 MB	42 MB	1.7 TB	N/A

- **Better Reasoning Capability:** neurosymbolic methods achieve high accuracy across reasoning tasks than NNs and human.
- **Smaller Memory Footprint:** neurosymbolic methods consume much less #parameter than NNs (e.g., LLM).

Evaluation – Hardware Performance

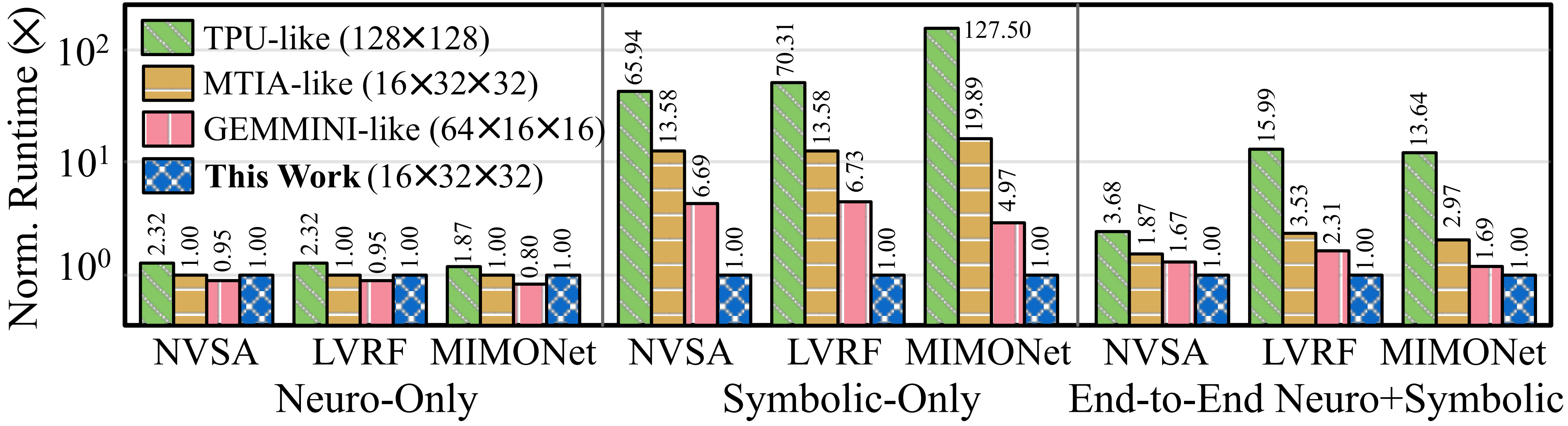


4x - 90x speedup
compared to CPU/GPU



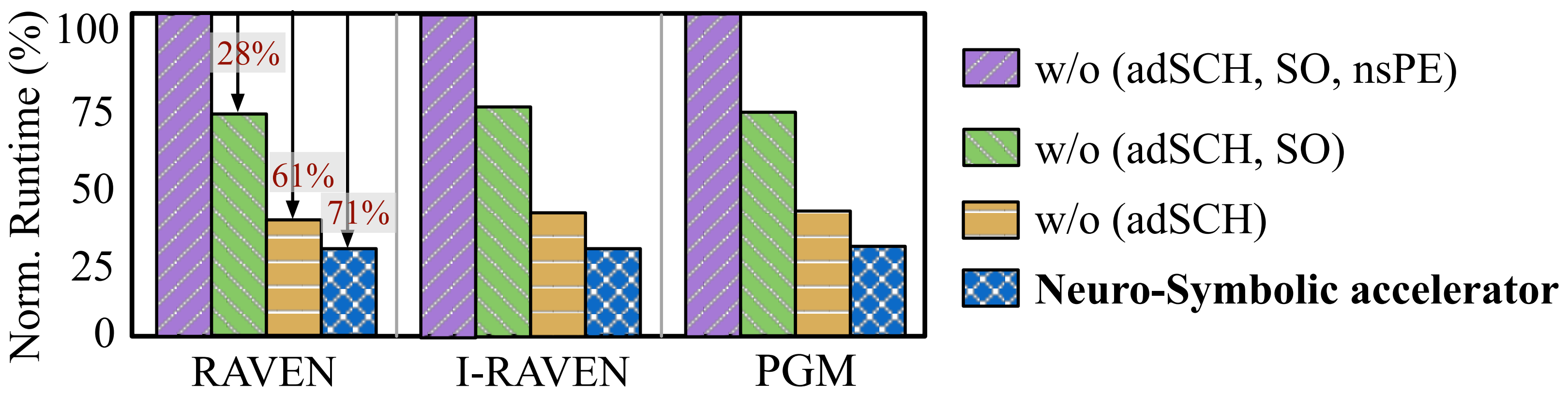
Symbolic operation:
75x speedup to TPU
18x speedup to GPU

Evaluation – Hardware Performance



Compared with ML accelerators: similar neuro latency, **7-120x symbolic** speedup, **2-16x end-to-end neuro-symbolic** speedup

Evaluation – Ablation Study



Proposed **scheduling**, reconfigurable **PE**, bubble streaming **dataflow** are effective

Neurosymbolic Cognitive Solution Algorithm @ Hardware	Normalized Runtime (%) on RAVEN	I-RAVEN	PGM	CVR	SVRT
NVSA @ Xavier NX	100	100	100	100	100
Proposed Algorithm @ Xavier NX	89.5%	88.9%	90.7%	87.6%	88.4%
Proposed Algorithm @ Proposed Accelerator	1.76%	1.74%	1.78%	1.72%	1.69%

Algorithm-system-hardware co-design is critical

😊 Key Observations:

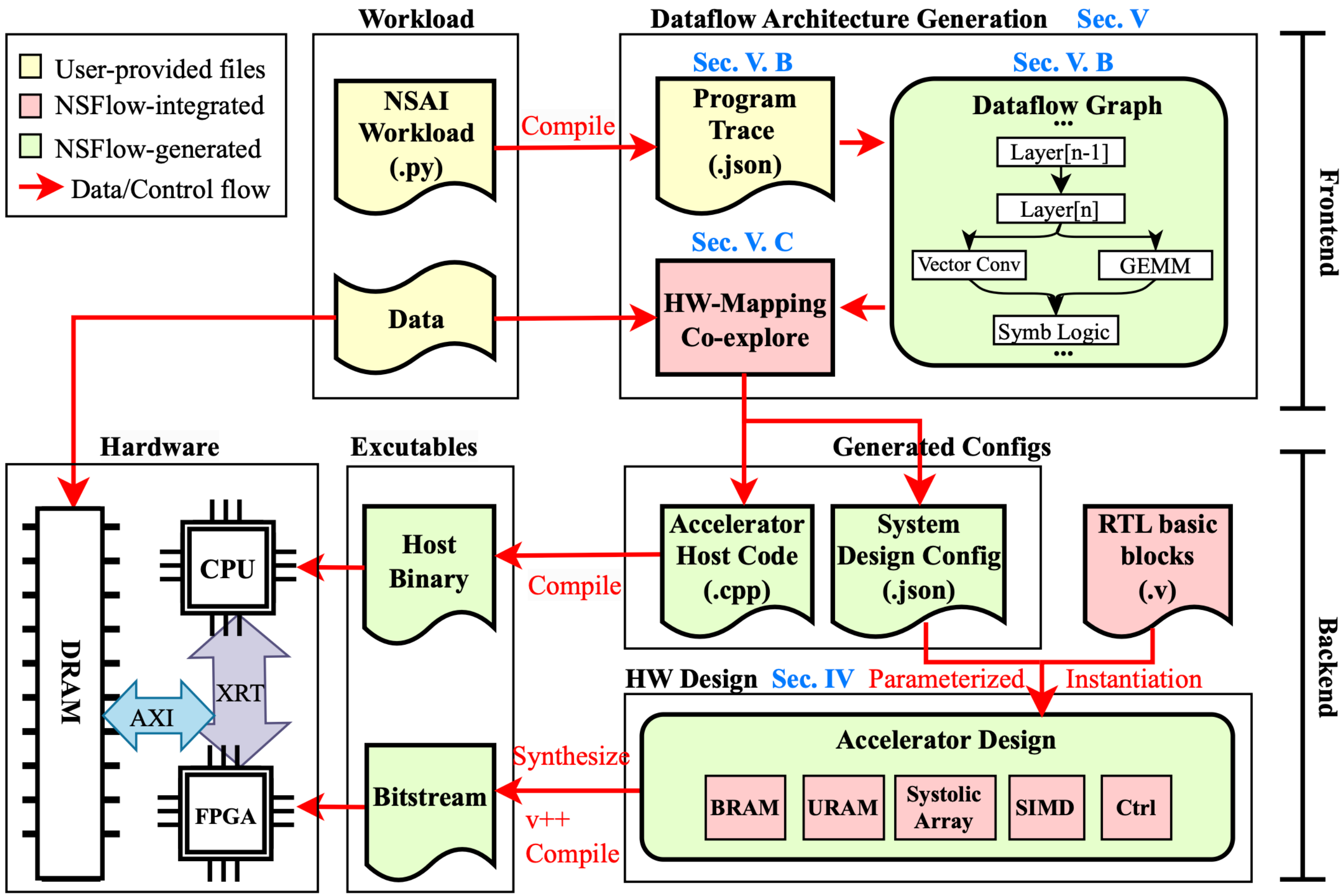
Compared with systolic arrays that only support neural, CogSys provides **reconfigurable support for neural and symbolic** operations with **only 4.8% area overhead**.

Our design achieves **0.3s latency** per cognition task, with **1.18W power** consumption.

Research Question:

How to **automate** this neuro-symbolic architecture **design** process?

End-to-End FPGA Deployment for Neuro-Symbolic AI



Frontend: dataflow arch generator
- Step 1: Extract execution trace
- Step 2: Generate dataflow graph
- Step 3: HW-mapping co-exploration

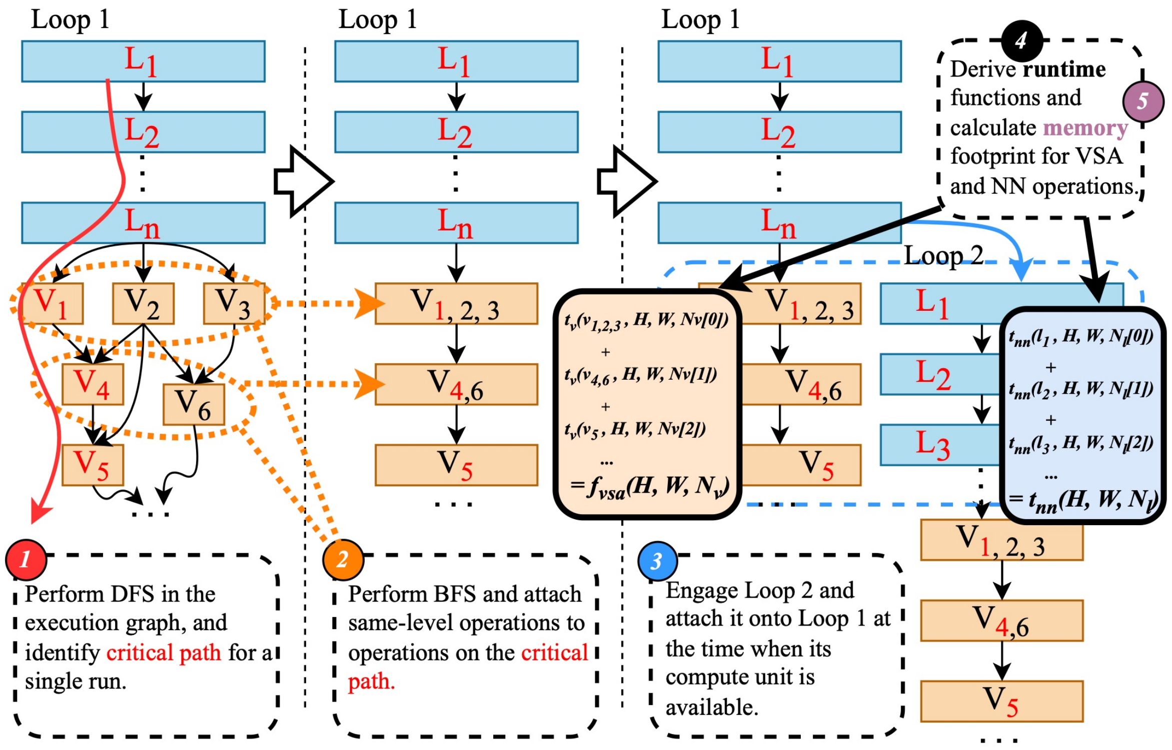
Backend: FPGA deployment
- Step 1: Pre-define hardware template
- Step 2: Configure design parameters
- Step 3: Synthesize and compile RTL

Hanchen Yang*, Zishen Wan*, Ritik Raj, Joongun Park, Ziwei Li, Ananda Samajdar, Arijit Raychowdhury, Tushar Krishna, **"NSFlow: An End-to-End FPGA Framework with Scalable Dataflow Architecture for Neuro-Symbolic AI "**, *to appear in* ***DAC 2025***

Frontend – Dataflow architecture Generation

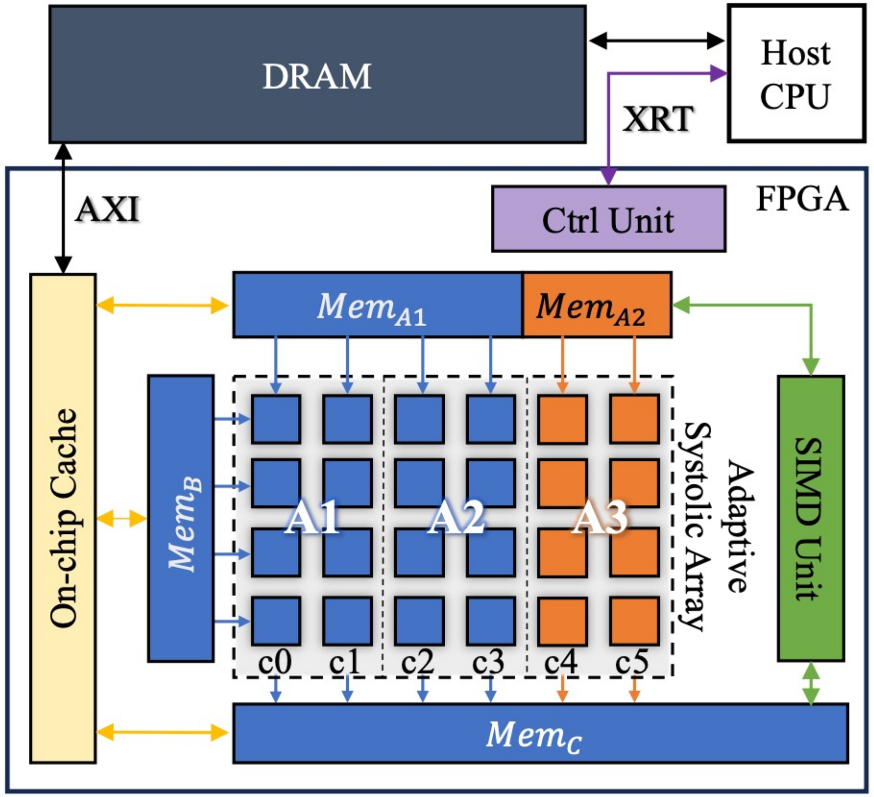
```
graph():
    ...
    // Neuro Operation - CNN (Resnet18)
    %relu_1[16,64,160,160] : call_module[relu](args = (%bn1
          [16,64,160,160]))
    %maxpool_1[16,64,160,160] : call_module[maxpool](args =
           (%relu_1[16,64,160,160]))
    %conv2d_1[16,64,160,160] : call_module[conv2d](args =
          (%maxpool_1[16,64,160,160]))
    ...
    // Symbolic Operations
    // Inverse binding of two block codes vectors by
         blockwise cicular correlation
    %inv_binding_circular_1[1,4,256] : call_function[nvsa.
         inv_binding_circular](args = (%vec_0[1,4,256], %
         vec_1[1,4,256]))
    %inv_binding_circular_2[1,4,256] : call_function[nvsa.
         inv_binding_circular](args = (%vec_3[1,4,256], %
         vec_4[1,4,256]))
    // Compute similarity between two block codes vectors
    %match_prob_1[1] : call_function[nvsa.match_prob](args
         = (%inv_binding_circular_1[1,4,256], %vec_2
          [1,4,256]))
    // Compute similarity between a dictionary and a batch
         of query vectors
    %match_prob_multi_batched_1[1]: call_function[nvsa.
         match_prob_multi_batched](args = (%
         inv_binding_circular_2[1,4,256], %vec_5[7,4,256]))
    %sum_1[1] : call_function[torch.sum](args = (%
         match_prob_multi_batched_1[1]))
    %clamp_1[1] : call_function[torch.clamp](args = (%sum_1
          [1]))
    %mul_1[1] : call_function[operator.mul](args = (%
         match_prob_1[1], %clamp_1[1]))
    ...
```

Extract workload execution trace

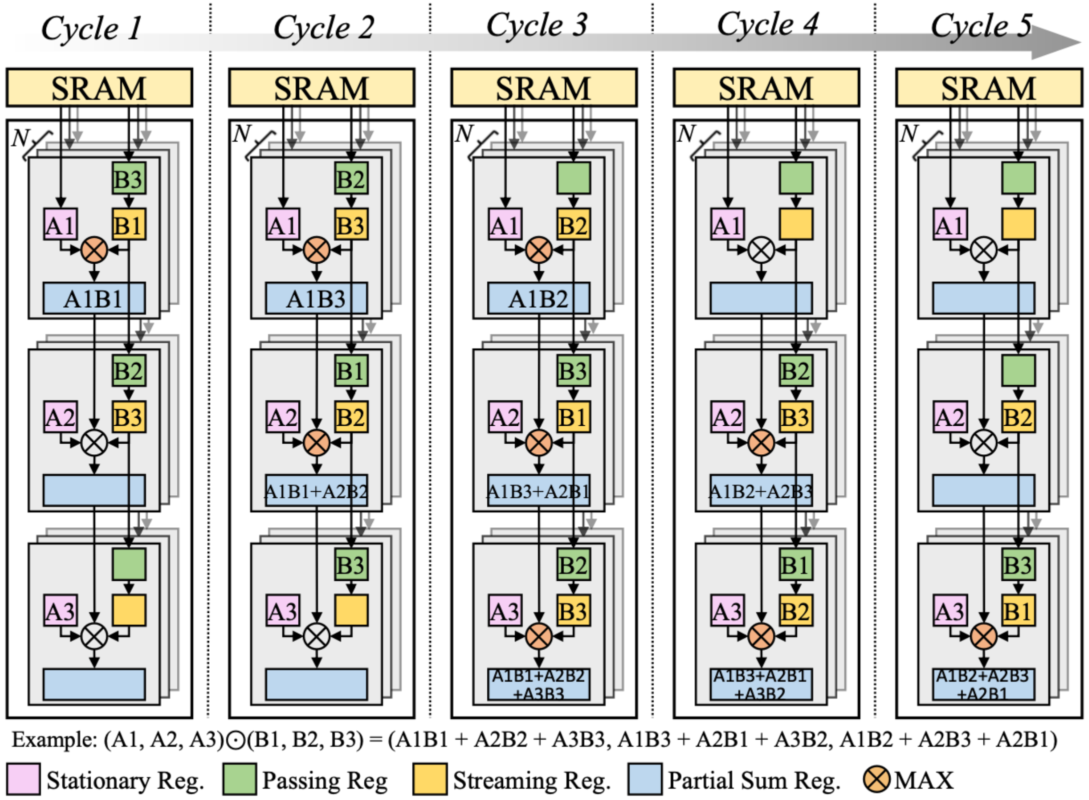


Generate dataflow graph &
two-stage HW-mapping co-exploration

Backend – FPGA Deployment

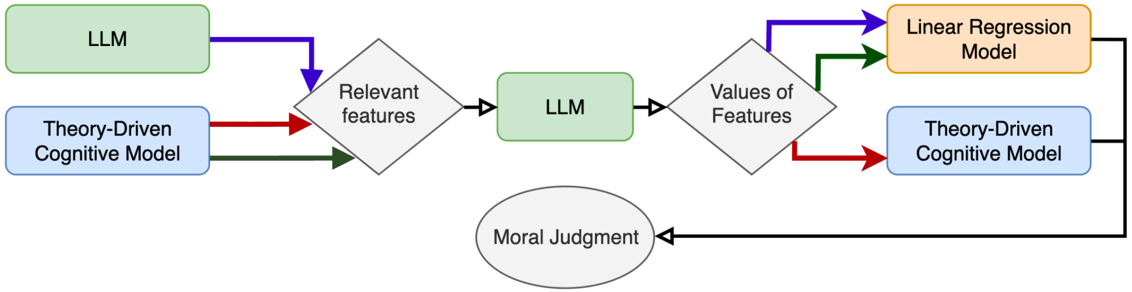


Pre-defined architecture template

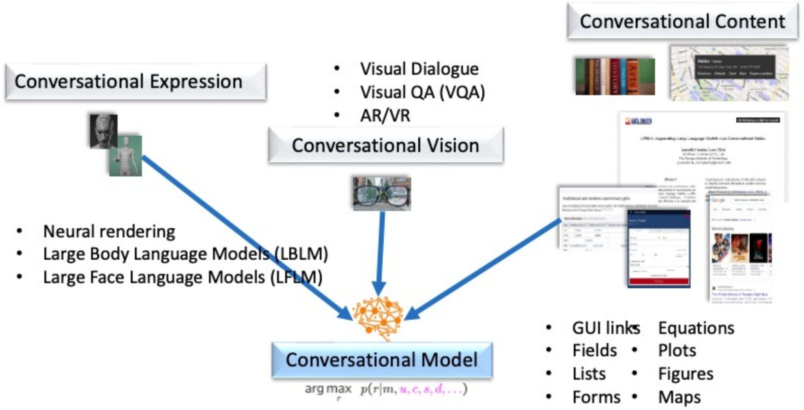


Dataflow & configure design parameters

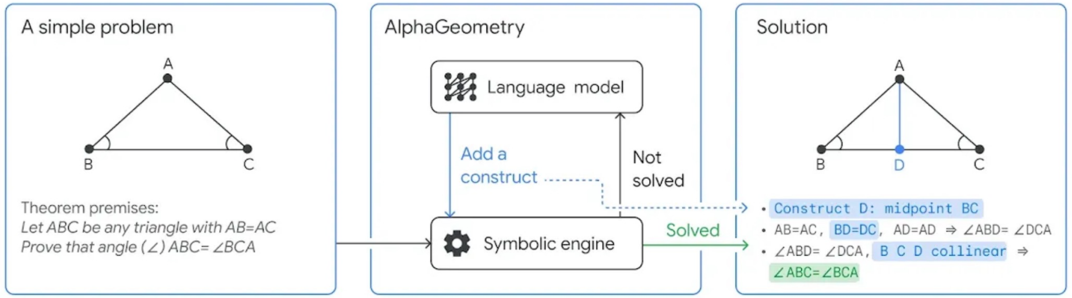
Looking Ahead: LLM + Neurosymbolic



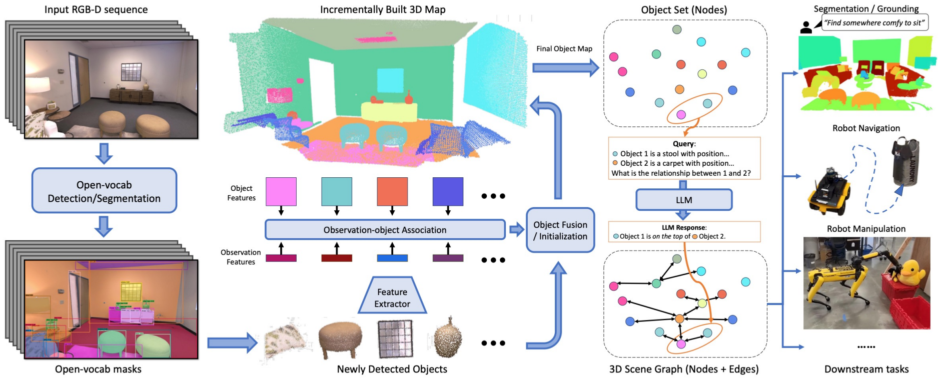
Towards safe and trustworthy AI System:
LLM + cognitive model for human moral judgment



Towards human-centered AI System:
LLM + knowledge base for conversational reasoning



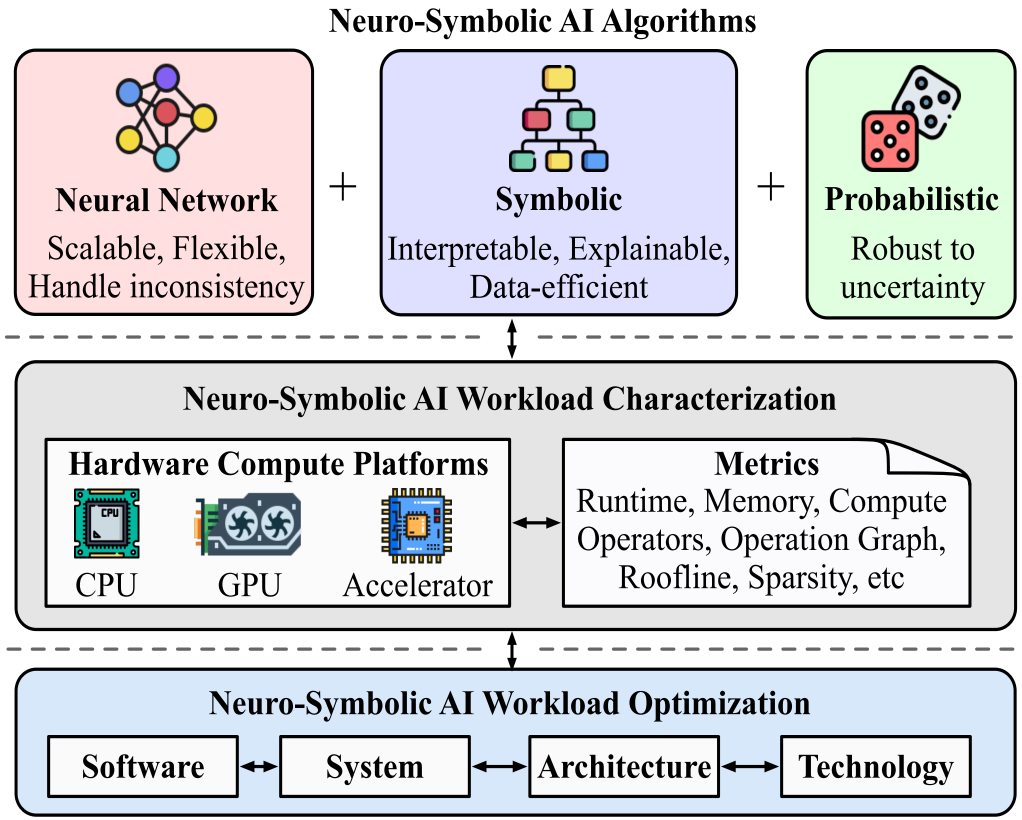
Towards logical reasoning AI System:
LLM + symbolic solver for scientific computing



Towards intelligent AI System:
LLM + concept graph for intelligent autonomous system

Summary

- **Motivation**
  - Neurosymbolic AI is a promising paradigm towards next-generation cognitive AI
  - Challenge: inefficiency on off-the-shelf hardware
- **Approach**
  - Characterize neurosymbolic workloads
  - Identify potential inefficiency reasons
  - Optimize neurosymbolic system via co-design.
- **Achieve**
  - Efficient and scalable neuro-symbolic execution across reasoning tasks.



https://synergy.ece.gatech.edu

Demystifying Neuro-Symbolic AI for Software-Hardware Co-Design

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MLBench Workshop @ ASPLOS, March 30, 2025