

Towards Cognitive AI Systems: A Survey and Prospective on Neuro-Symbolic AI

Zishen Wan, Che-Kai Liu*, Hanchen Yang*, Chaojian Li*, Haoran You*, Yonggan Fu,
Cheng Wan, Tushar Krishna, Yingyan (Celine) Lin, Arijit Raychowdhury

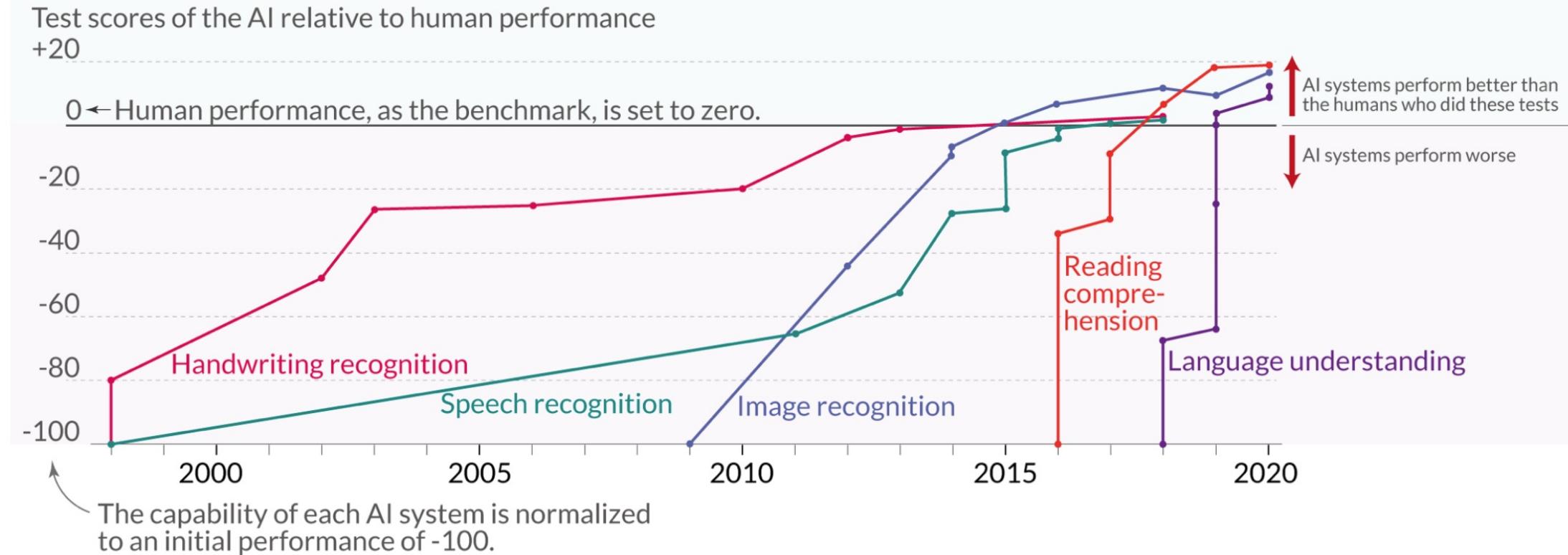
Georgia Institute of Technology, Atlanta, GA



State of AI / Landscape

Language and image recognition capabilities of AI systems have improved rapidly

Our World
in Data



Data source: Kiela et al. (2021) – Dynabench: Rethinking Benchmarking in NLP

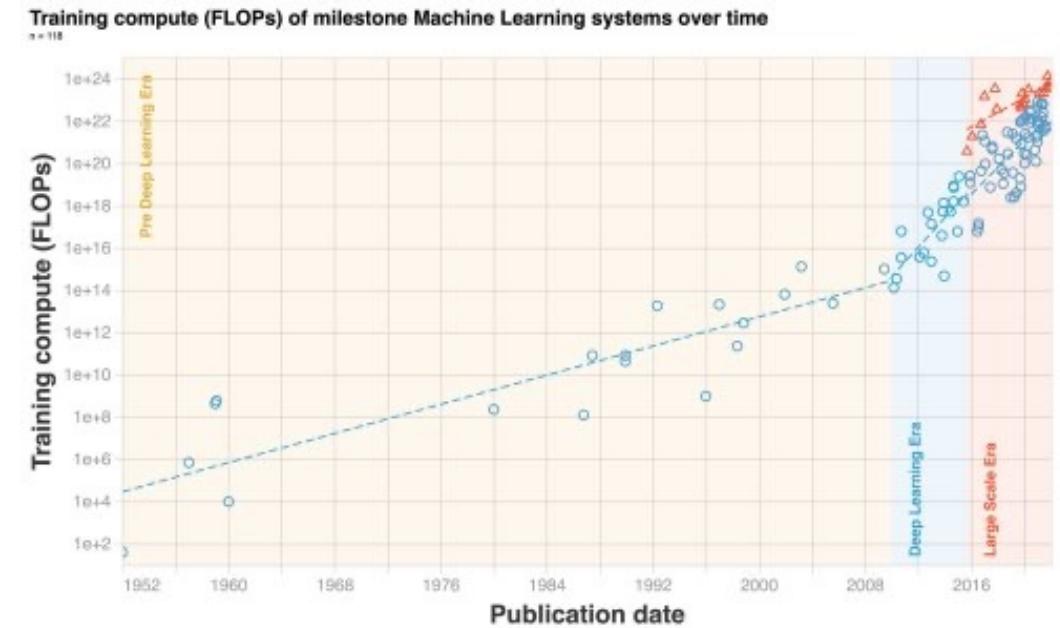
OurWorldInData.org – Research and data to make progress against the world's largest problems.

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AI Challenges

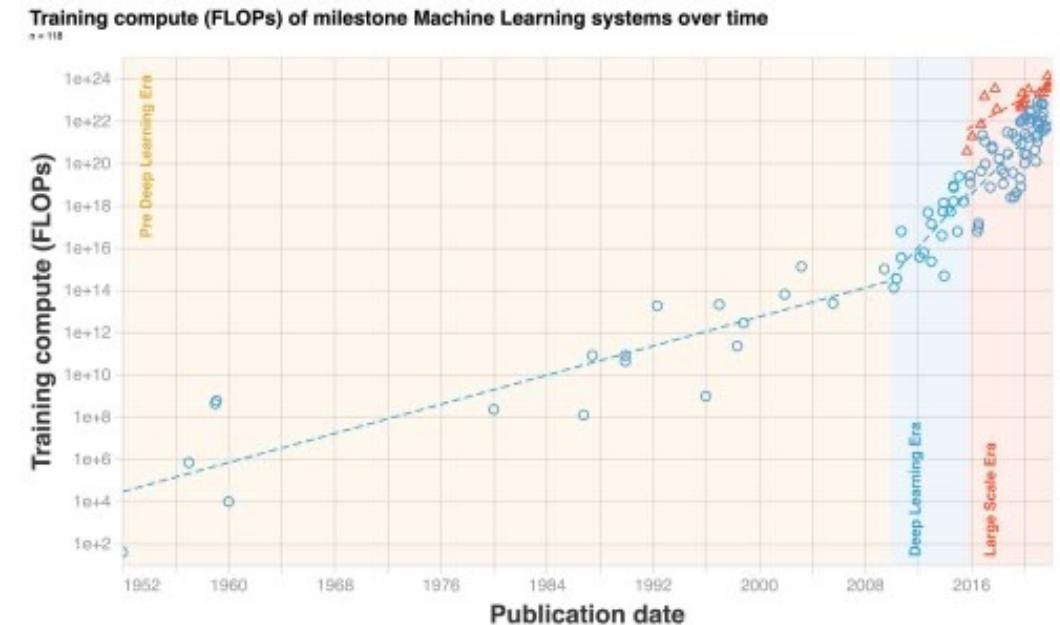
AI Challenges

- Unsustainable compute trajectory



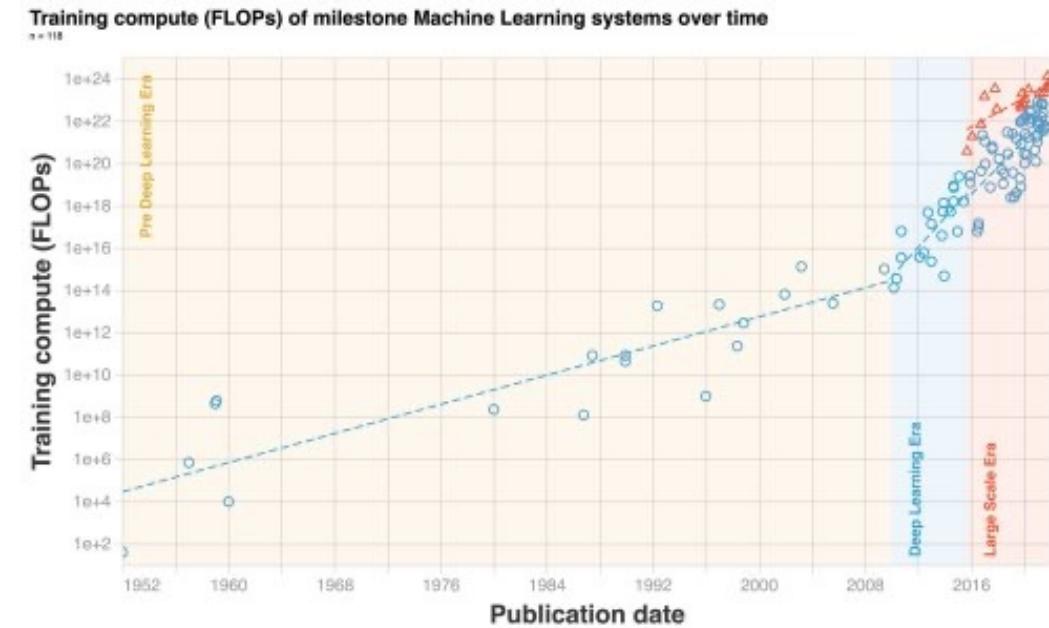
AI Challenges

- Unsustainable compute trajectory
- Lack of explainability and transparency



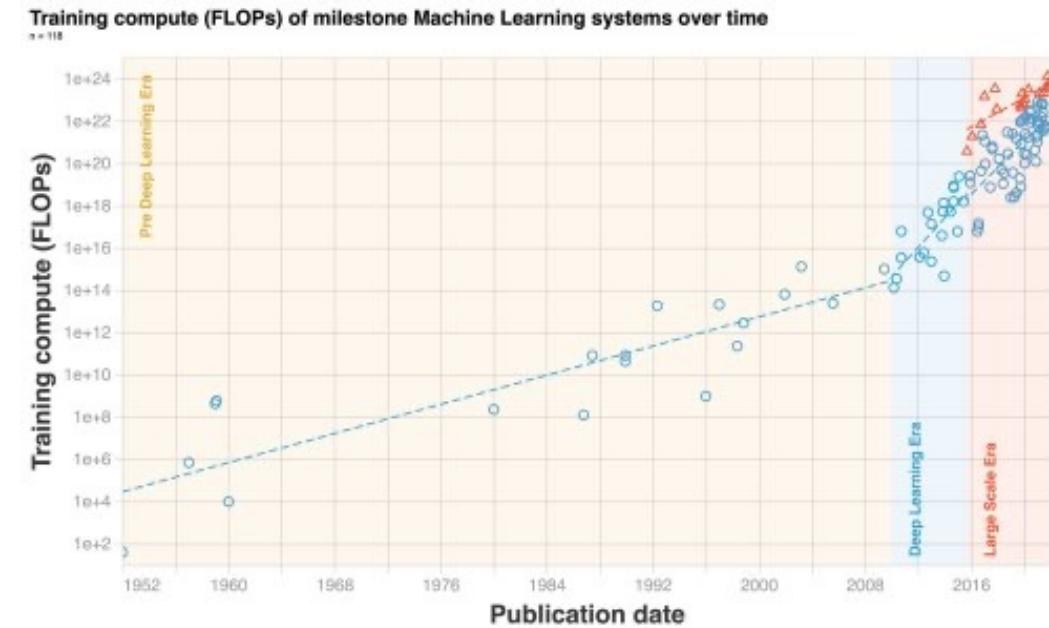
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- Unsustainable compute trajectory
- Lack of explainability and transparency
- Lack of robustness and reliability



AI Challenges

- Unsustainable compute trajectory
- Lack of explainability and transparency
- Lack of robustness and reliability
- Struggle in some tasks

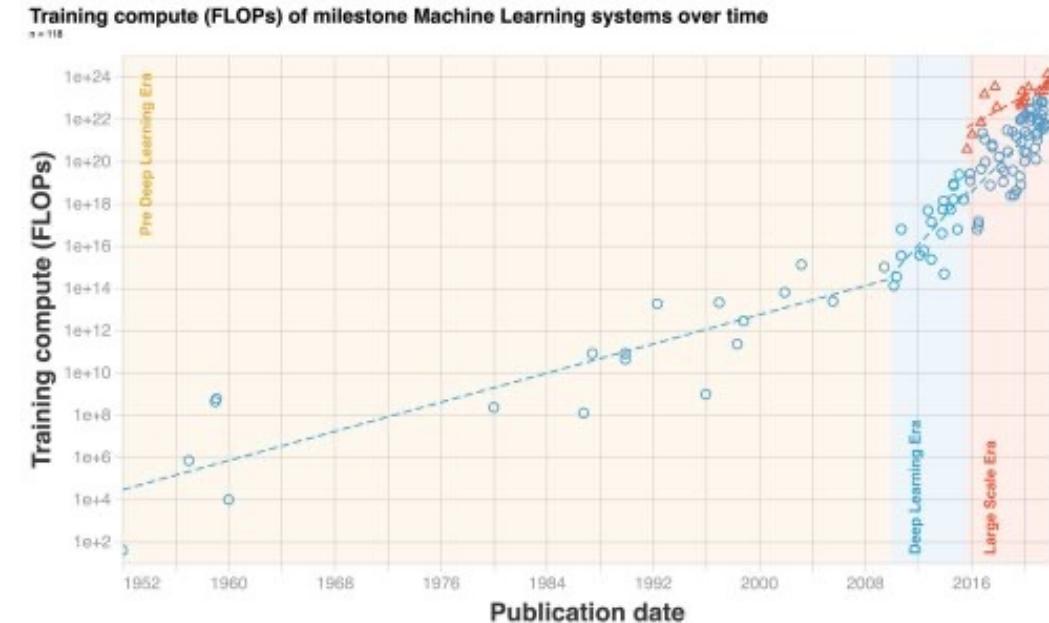


AI Challenges

- Unsustainable compute trajectory
- Lack of explainability and transparency
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- Struggle in some tasks



Are there more trees
than animals?



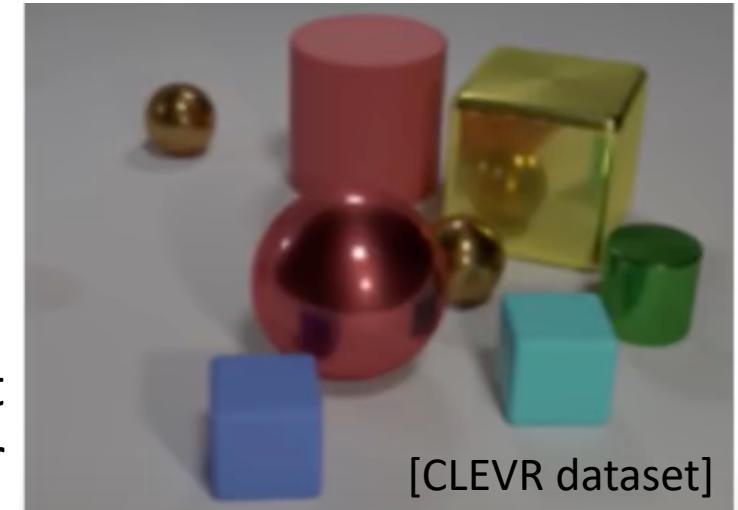
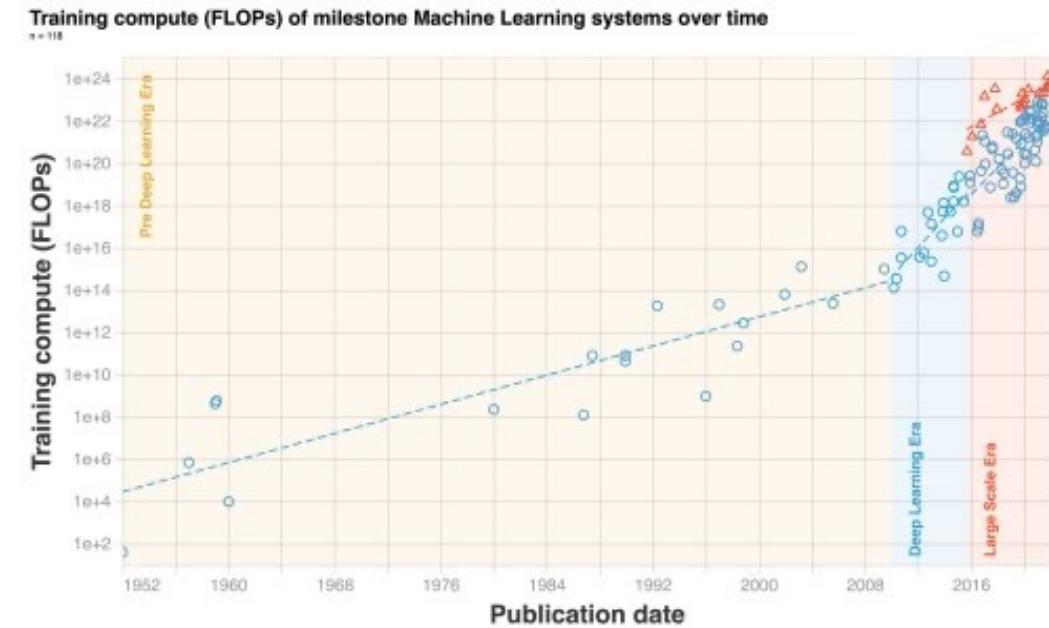
AI Challenges

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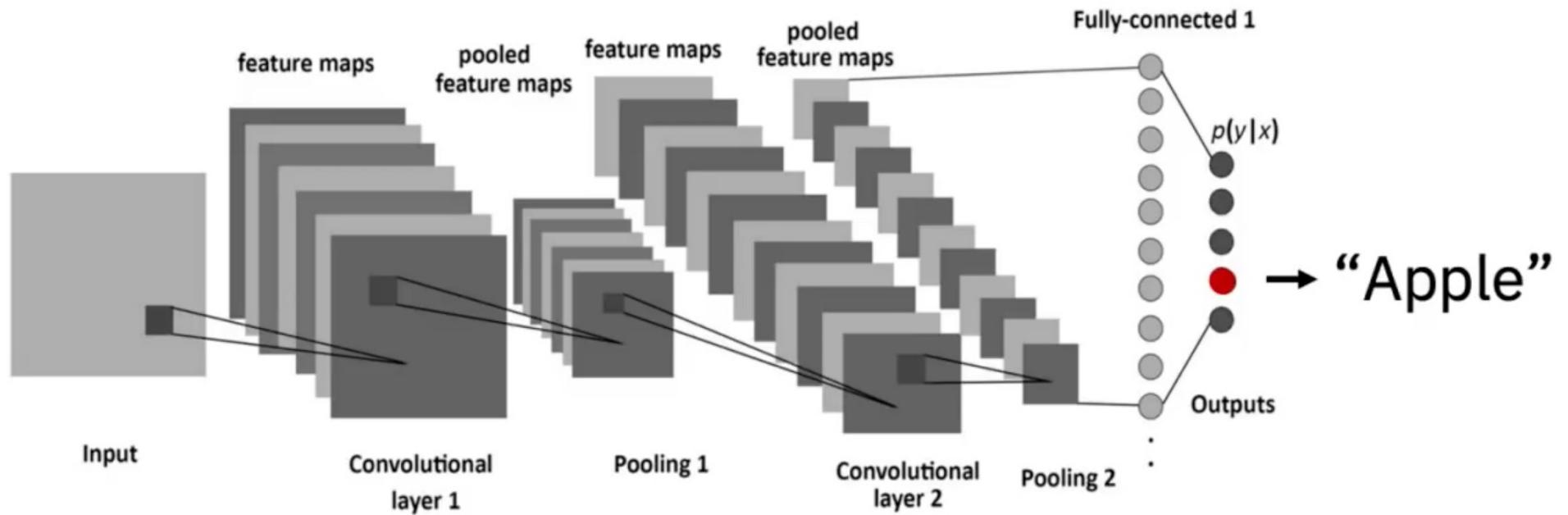


Are there more trees
than animals?

What's the shape of object
closest to large cylinder

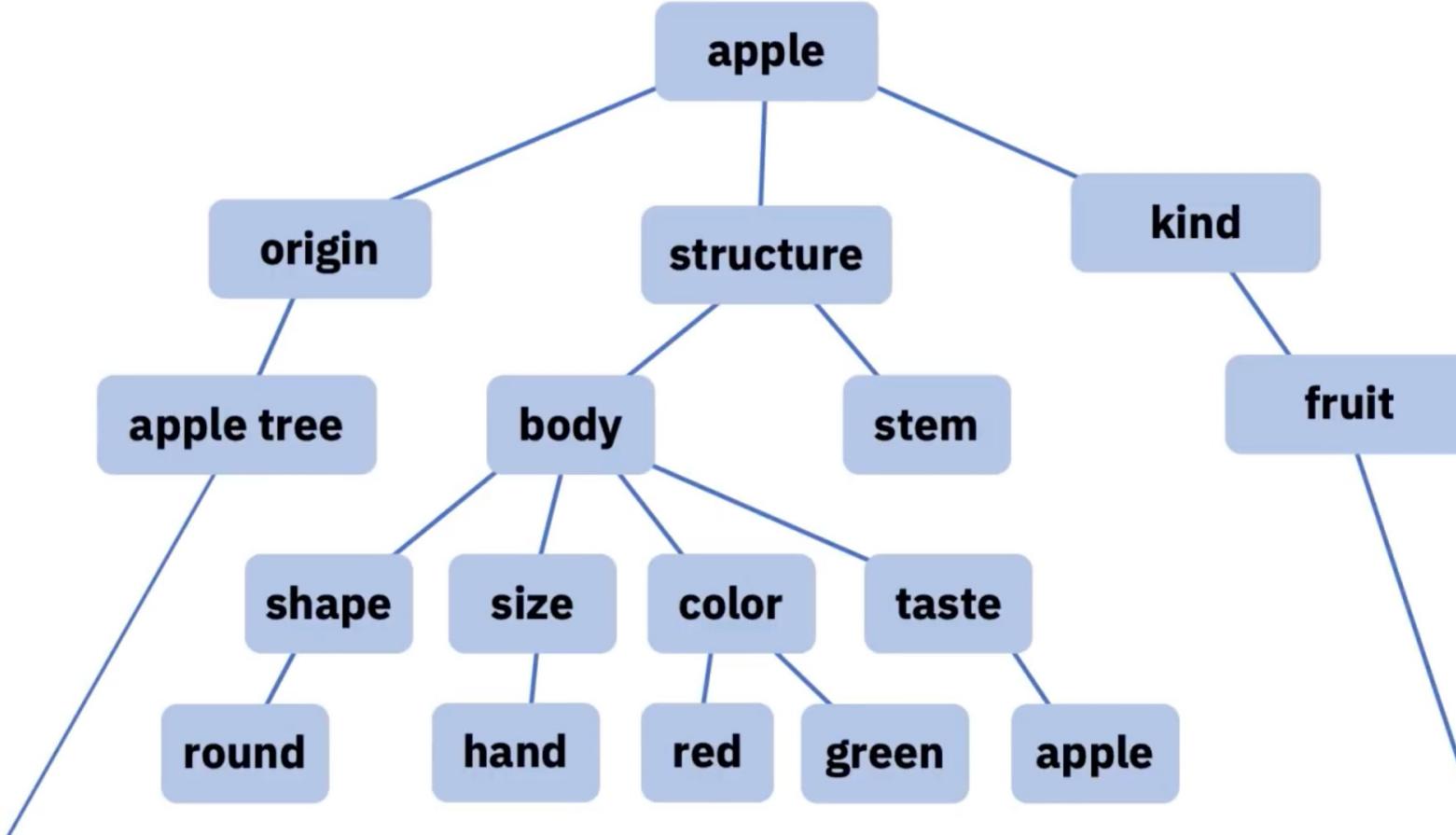


Neural Networks / Deep Learning



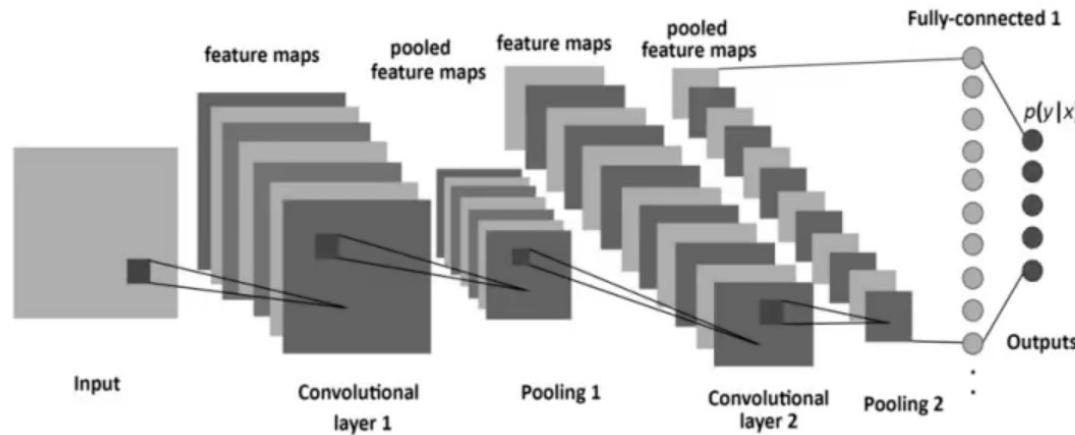
[Credit to MIT 6.S191, David Cox]

Symbolic AI



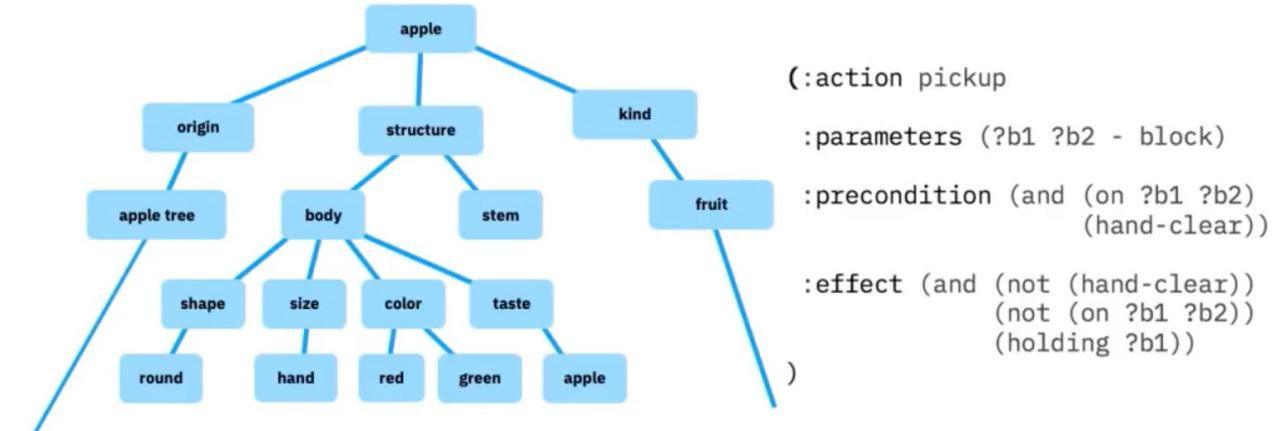
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Neuro-Symbolic AI



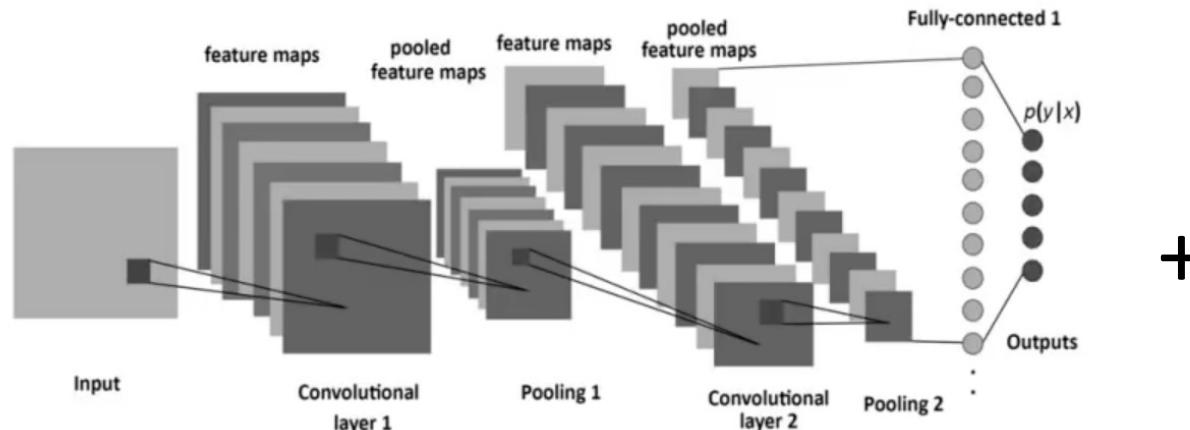
Neural Network

+



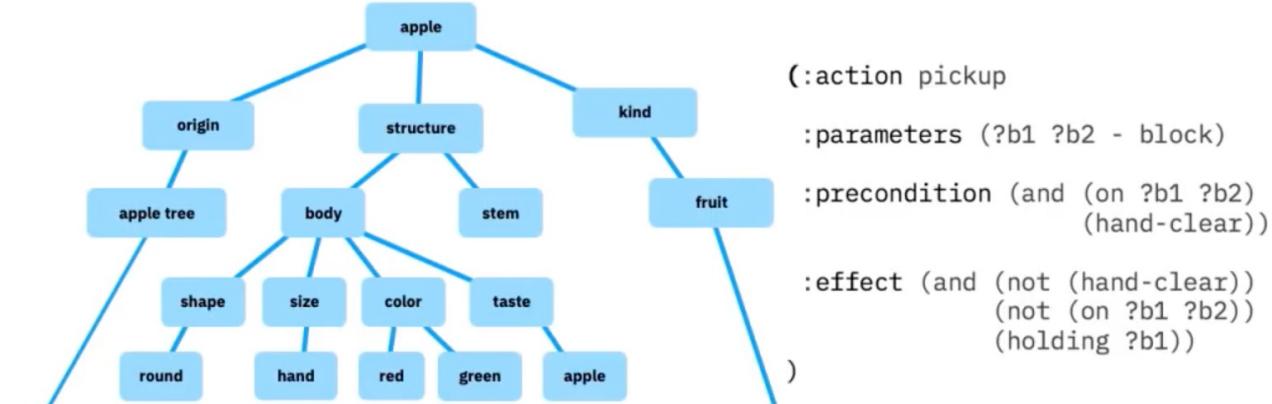
Symbolic AI

Neuro-Symbolic AI



Neural Network

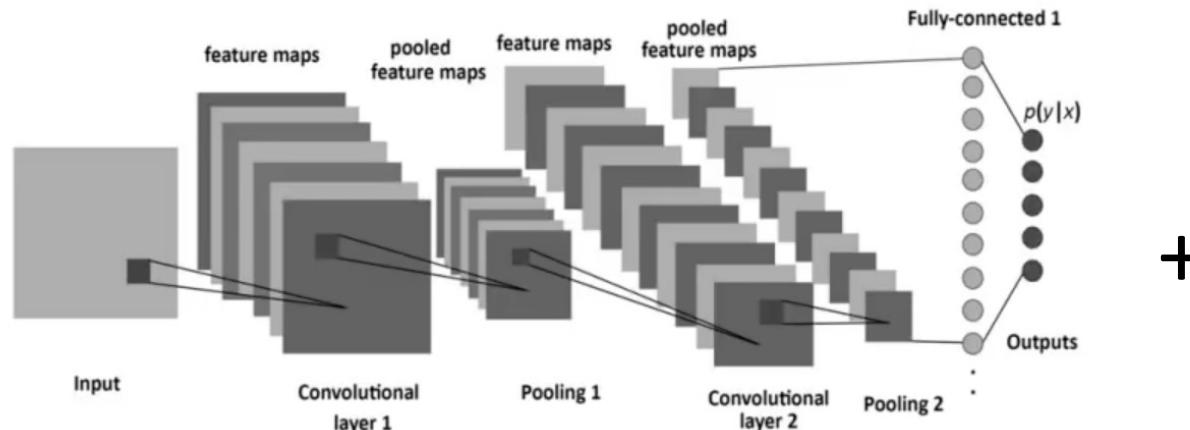
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Symbolic AI

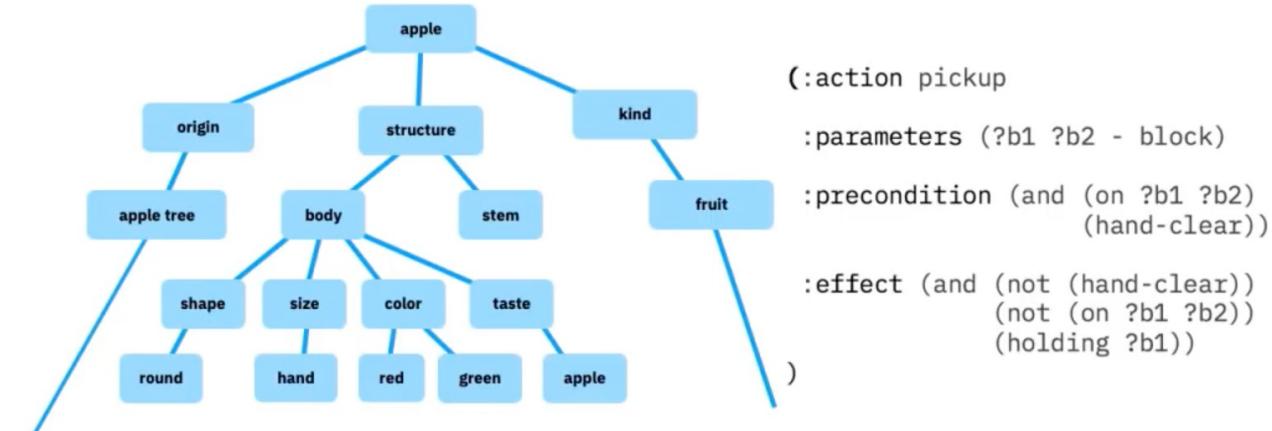
- Features
 - **Neuro**: scalable, flexible, handle inconsistency
 - **Symbolic**: interpretable, explainable, data-efficient

Neuro-Symbolic AI



Neural Network

+



Symbolic AI

- Features
 - **Neuro**: scalable, flexible, handle inconsistency
 - **Symbolic**: interpretable, explainable, data-efficient

- Advantages:
 - Improve efficiency, robustness, and explainability
 - Human-like **reasoning** and **cognition** capability

Towards Understanding the Computational Characteristics of Neuro-Symbolic Workloads

- Very little understanding exists of the computational characteristics of neuro-symbolic AI workloads

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Step 1: Categorizing Neuro-Symbolic AI **Algorithm**

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Step 2: Benchmarking selecting algorithms on current **Hardware**

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Step 3: Our view for Neuro-Symbolic AI **Challenges and Opportunities**

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- Very little understanding exists of the computational characteristics of neuro-symbolic AI workloads



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Step 2: Benchmarking selecting algorithms on current **Hardware**



Step 3: Our view for Neuro-Symbolic AI **Challenges and Opportunities**

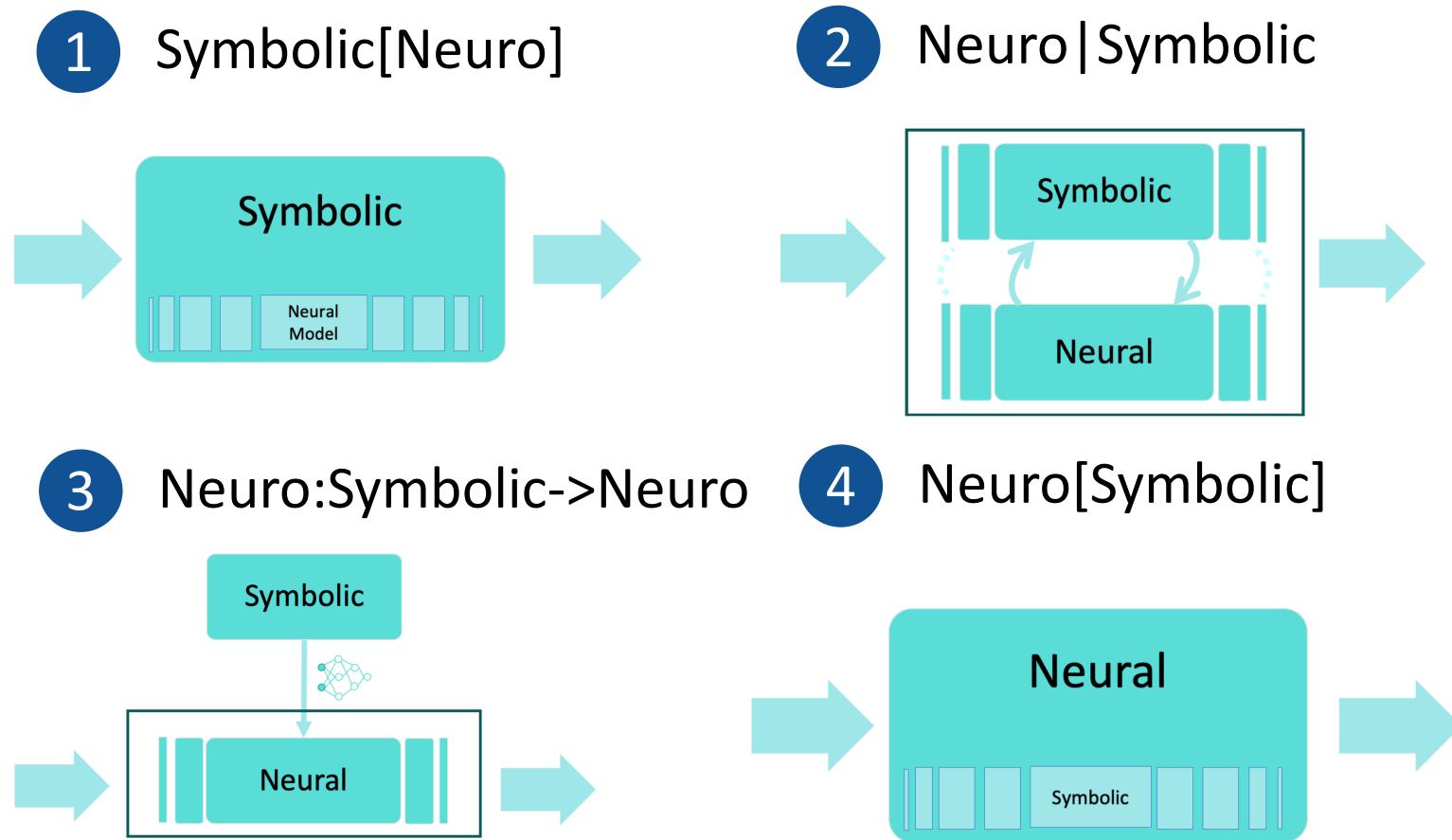
Neuro-Symbolic AI Algorithms

- **Classification Criterion:**

How neuro-symbolic integrated into a cohesive system
(Henry Kautz's taxonomy)

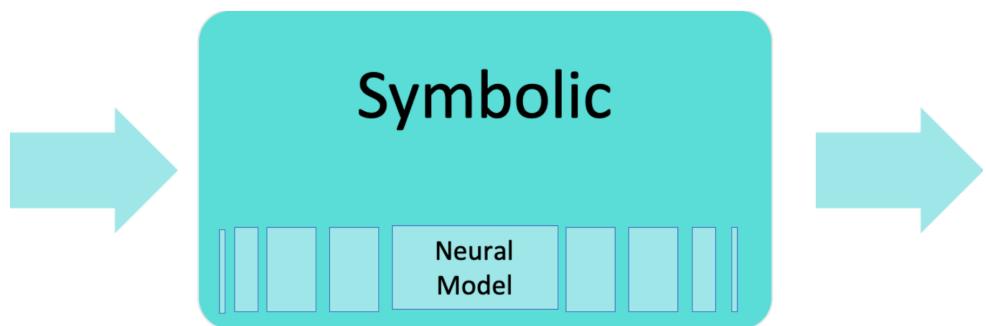
Neuro-Symbolic AI Algorithms

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Neuro-Symbolic AI Algorithms

1 Symbolic[Neuro]



Example:

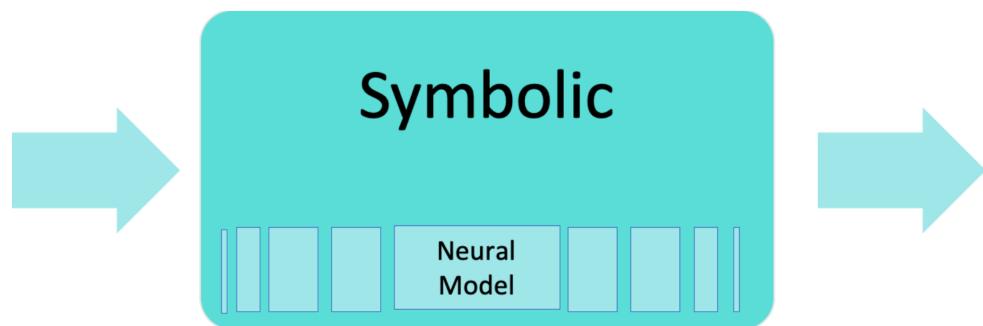
AlphaGo^[1]

AlphaZero^[2]

[1] Nature 2017; [2] Nature 2020

Neuro-Symbolic AI Algorithms

1 Symbolic[Neuro]



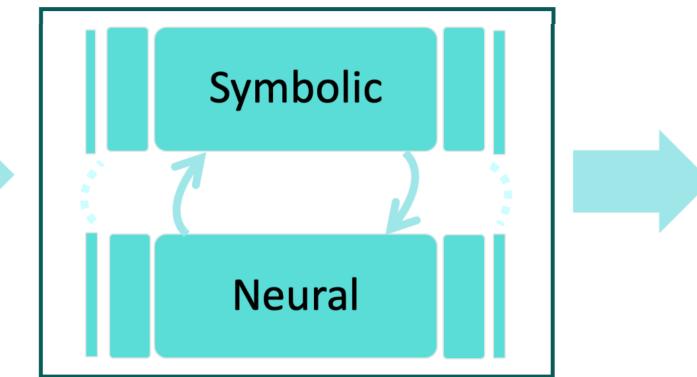
Example:

AlphaGo^[1]

AlphaZero^[2]

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2 Neuro | Symbolic



Example:

neuro-vector-symbolic architecture^[3]

neuro-probabilistic logic programming^[4]

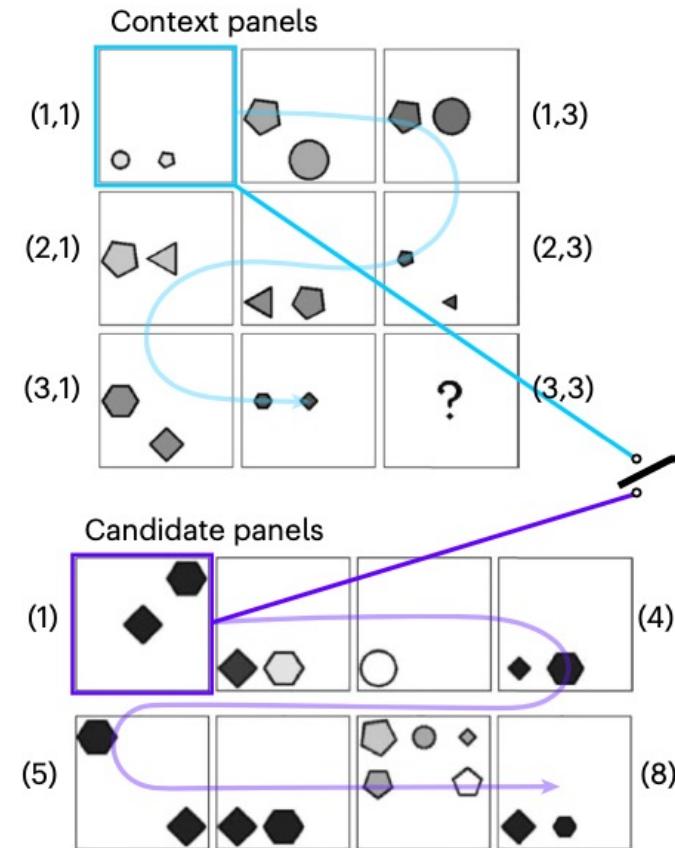
neuro-symbolic dynamic reasoning^[5]

[3] Nature 2023; [4] AI 2021; [5] ICLR 2020

Neuro | Symbolic Example

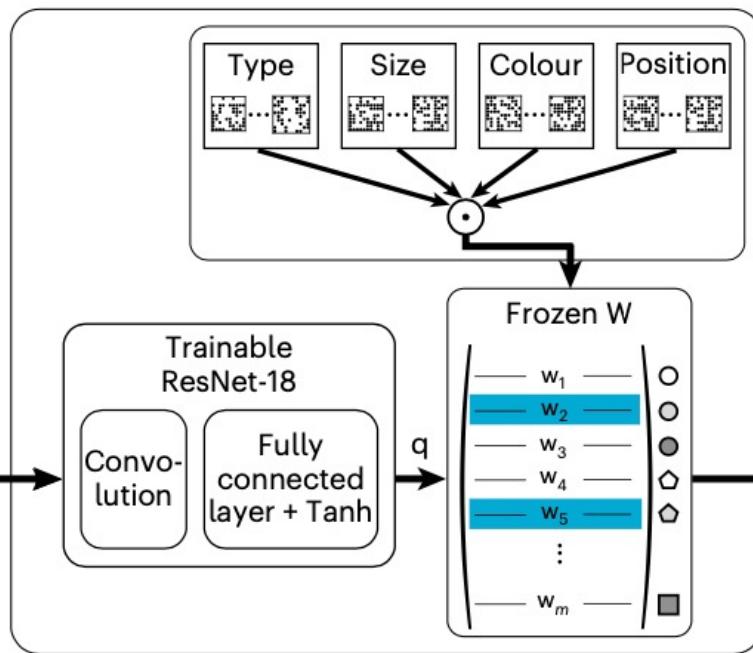
a

RAVEN example test



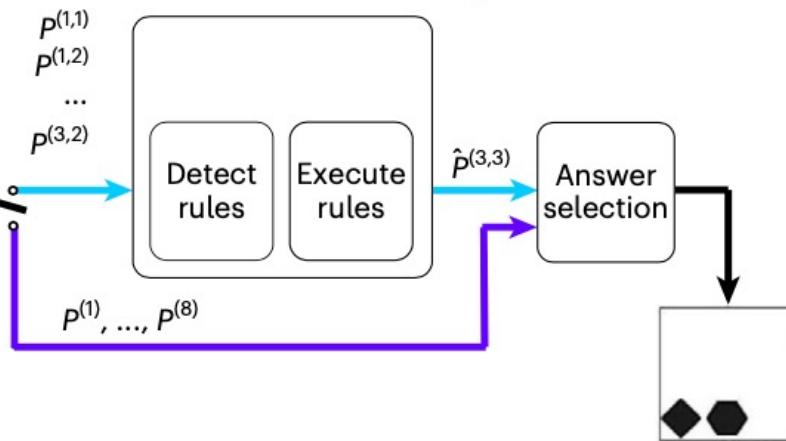
b

NVSA frontend: perception



c

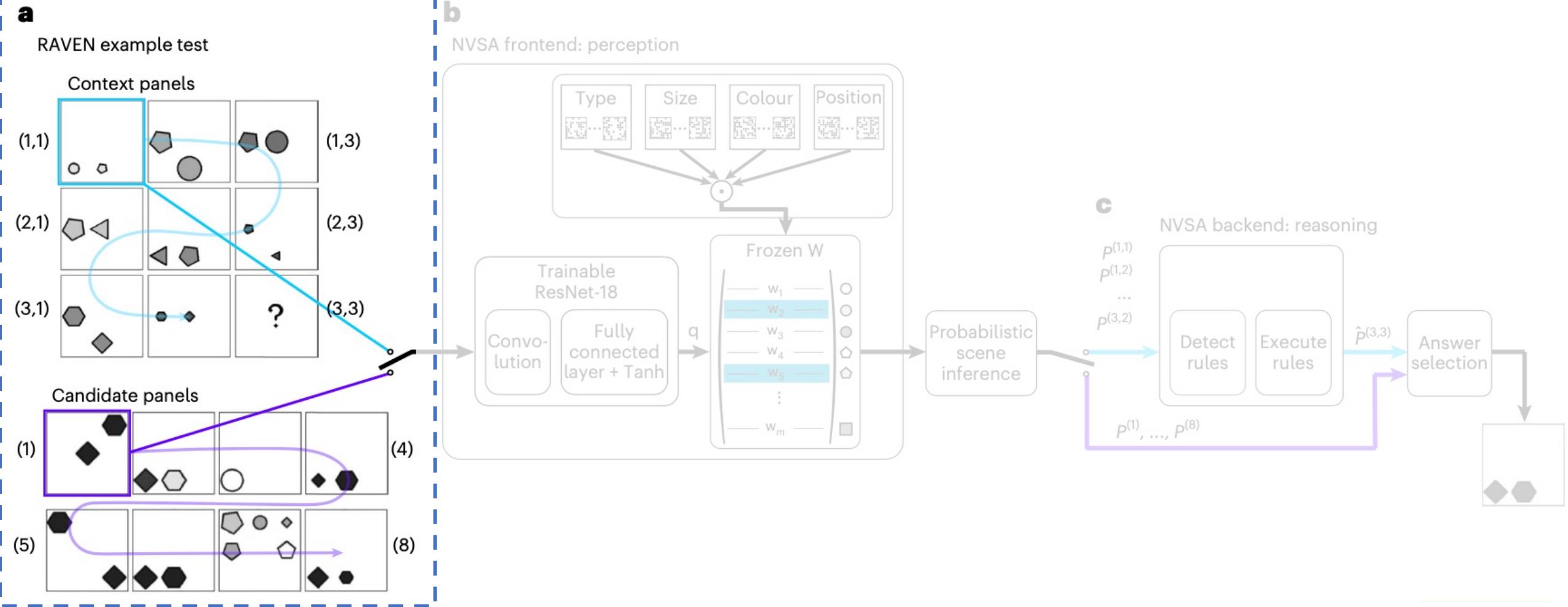
NVSA backend: reasoning



Neuro-vector-symbolic architecture

[M. Hersche, et al., Nature Machine Intelligence 2023]

Neuro | Symbolic Example

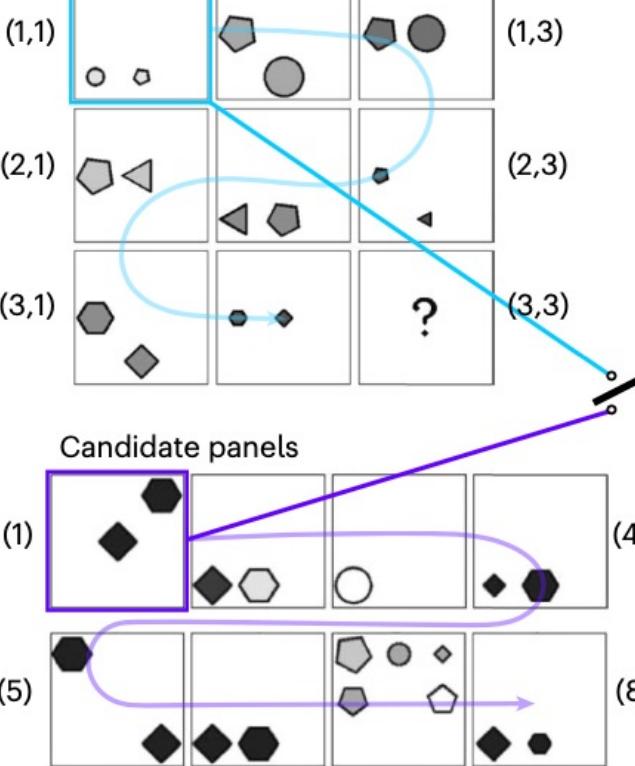


Neuro | Symbolic Example

a

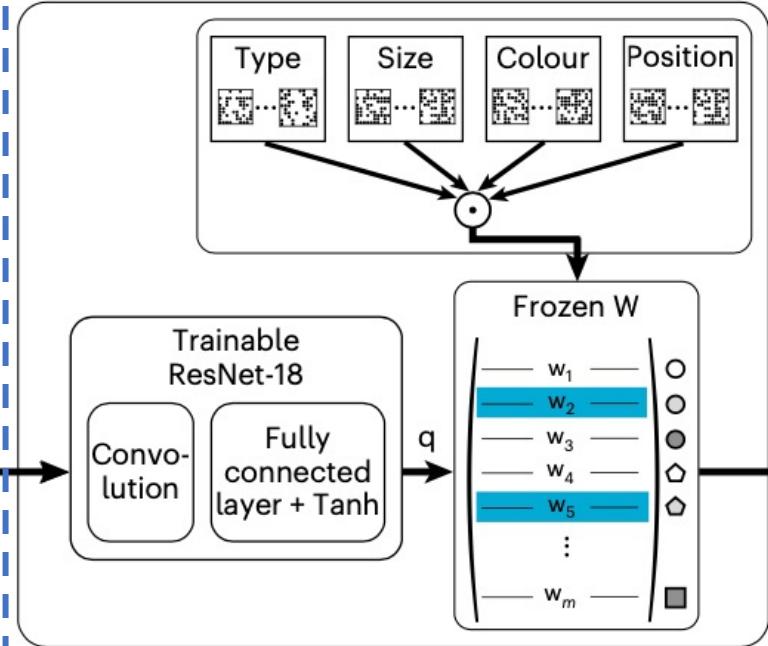
RAVEN example test

Context panels

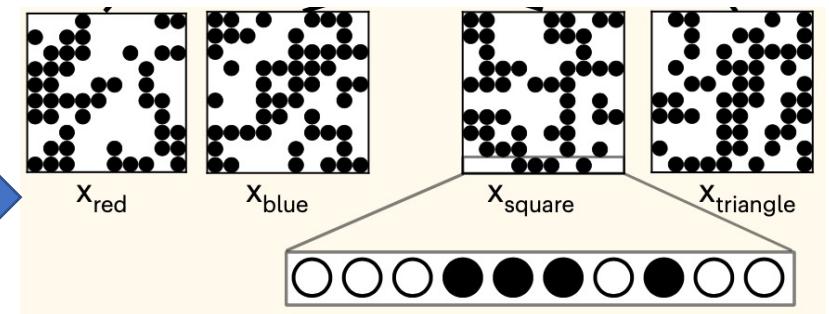


b

NVSA frontend: perception

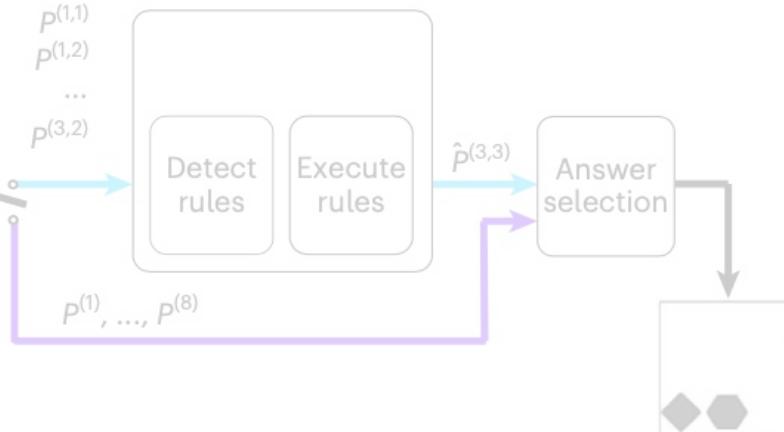


Neuro - Perception



c

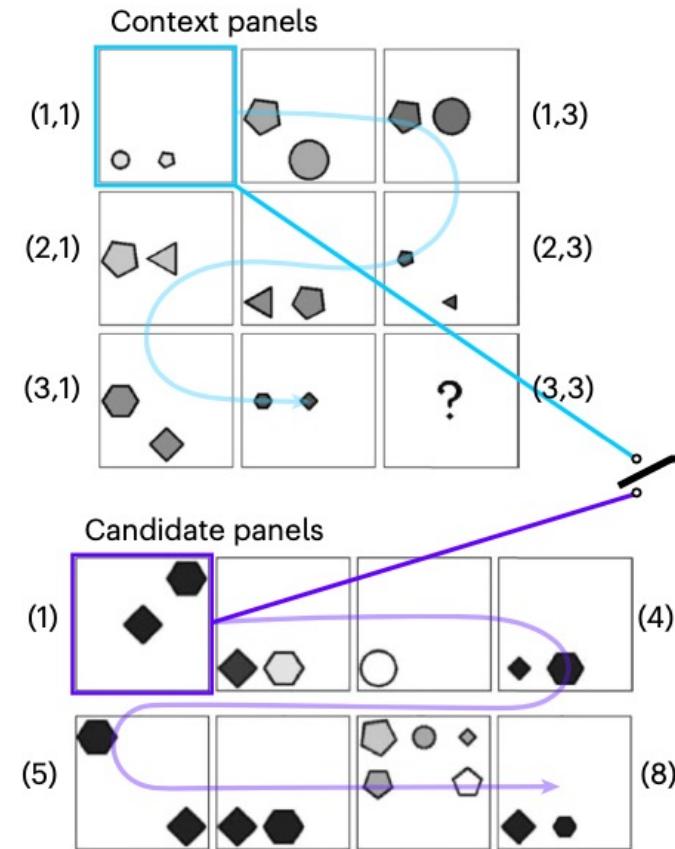
NVSA backend: reasoning



Neuro | Symbolic Example

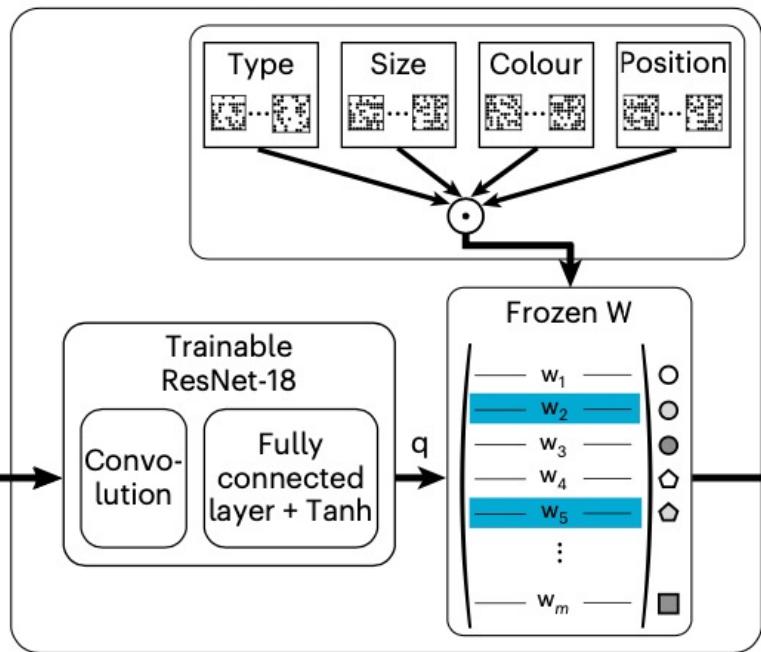
a

RAVEN example test



b

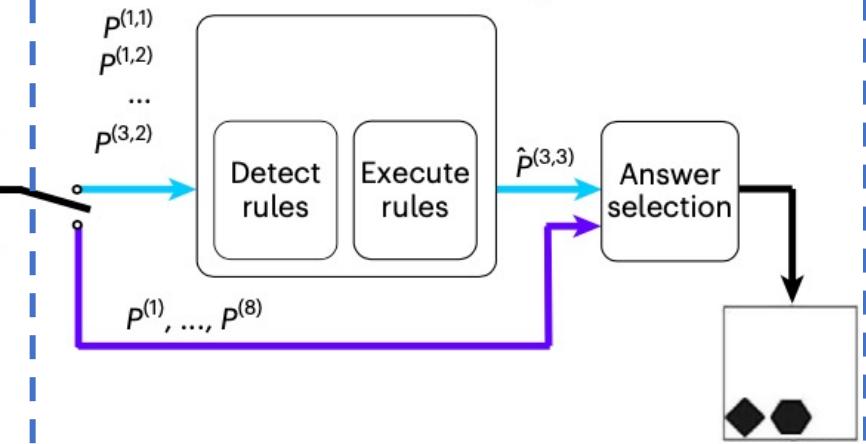
NVSA frontend: perception



VSA algebra

c

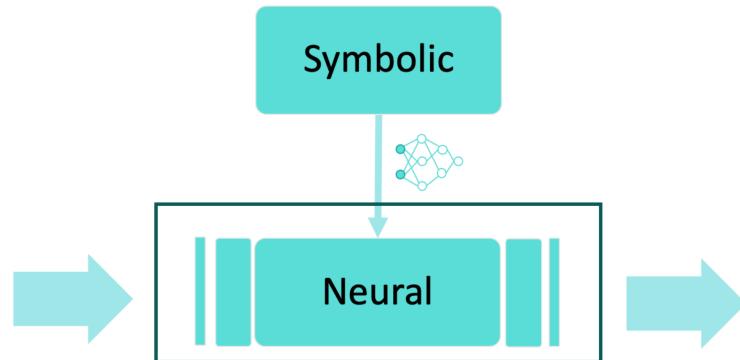
NVSA backend: reasoning



Symbolic - Reasoning

Neuro-Symbolic AI Algorithms

3 Neuro:Symbolic -> Neuro



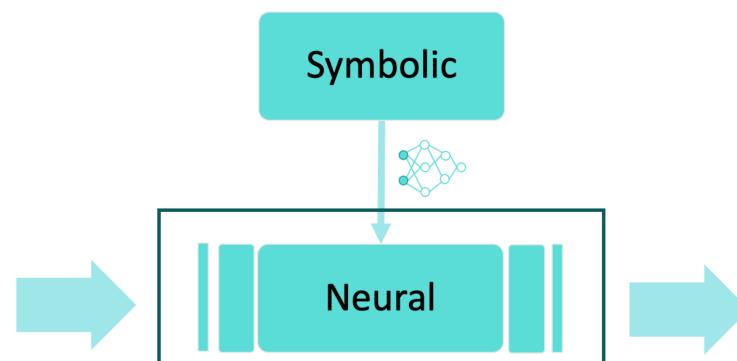
Example:

logical neural network^[6]

Inductive logic programming^[7]

Neuro-Symbolic AI Algorithms

3 Neuro:Symbolic -> Neuro

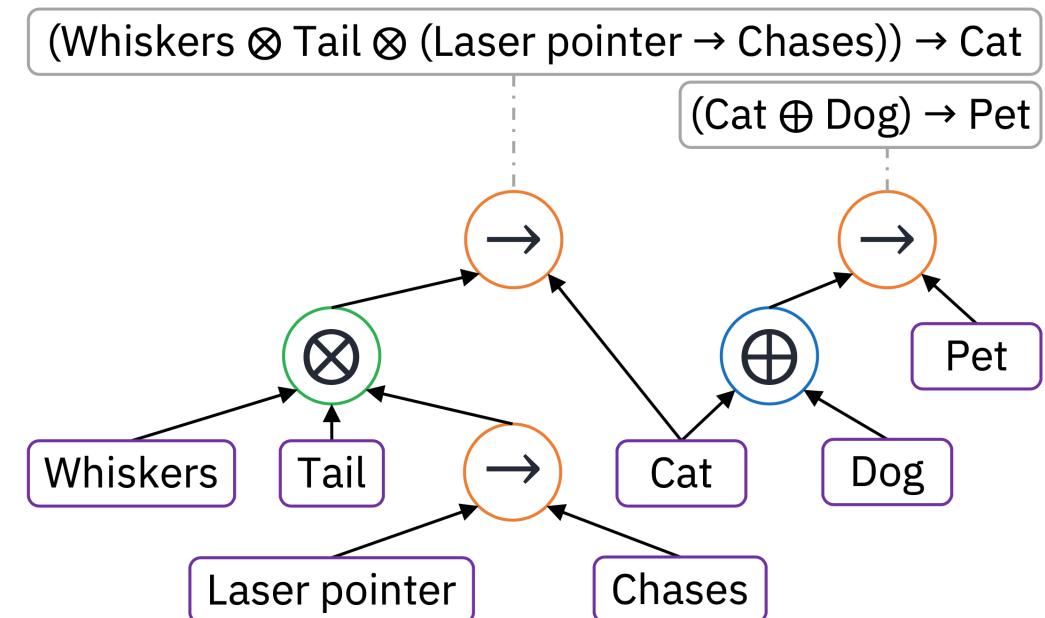


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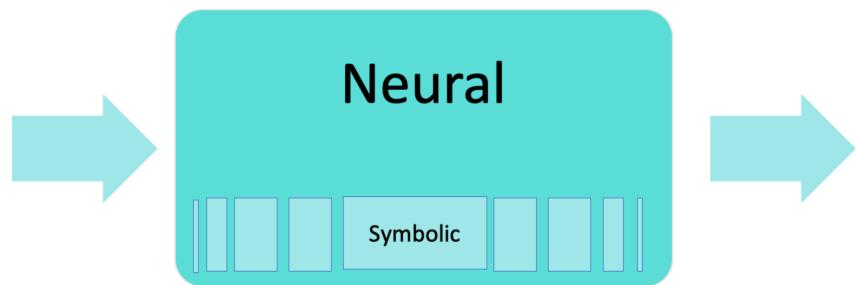
[6] NeurIPS 2020; [7] JAIR 2018



logical neural network^[6]

Neuro-Symbolic AI Algorithms

4 Neuro[Symbolic]

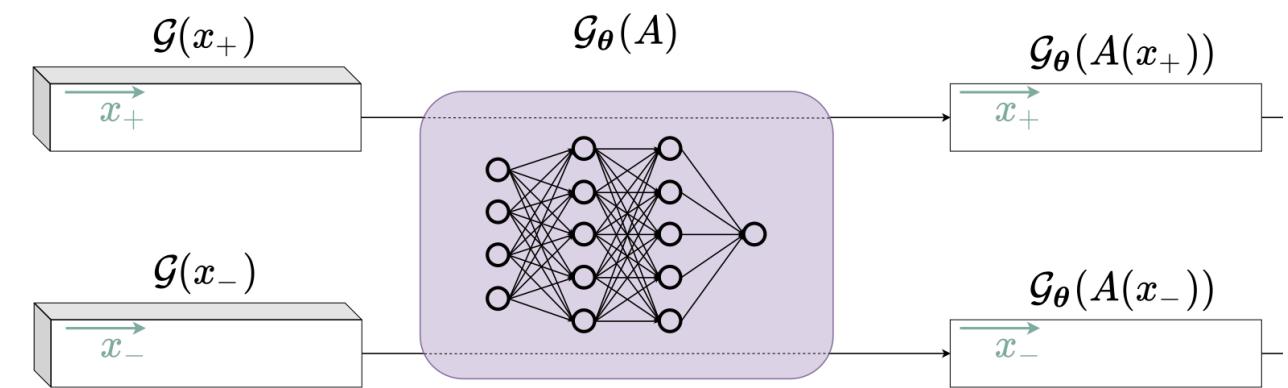
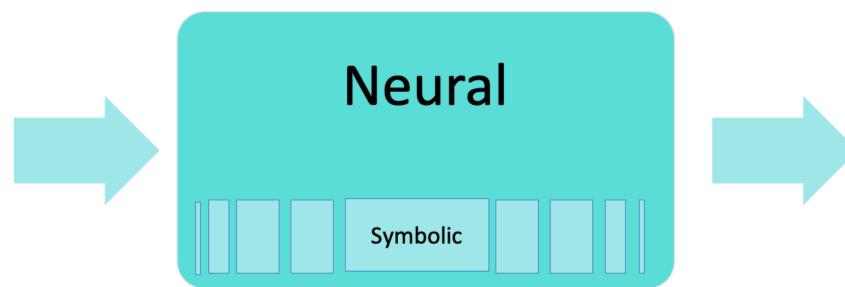


Example:
logical tensor network^[8]
deep ontology network^[9]

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Neuro-Symbolic AI Algorithms

4 Neuro[Symbolic]



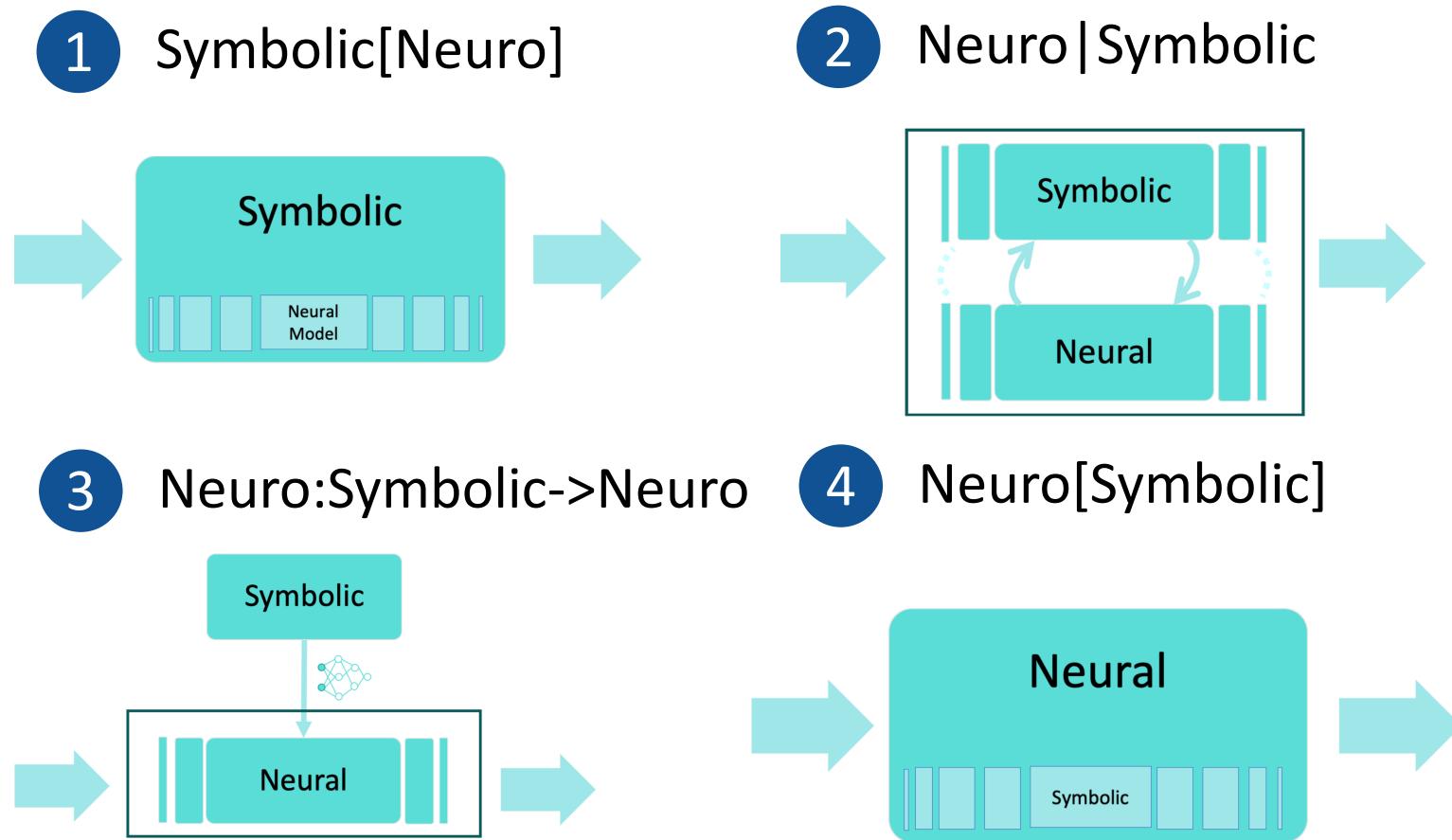
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Step 2: Benchmarking selecting algorithms on current **Hardware**

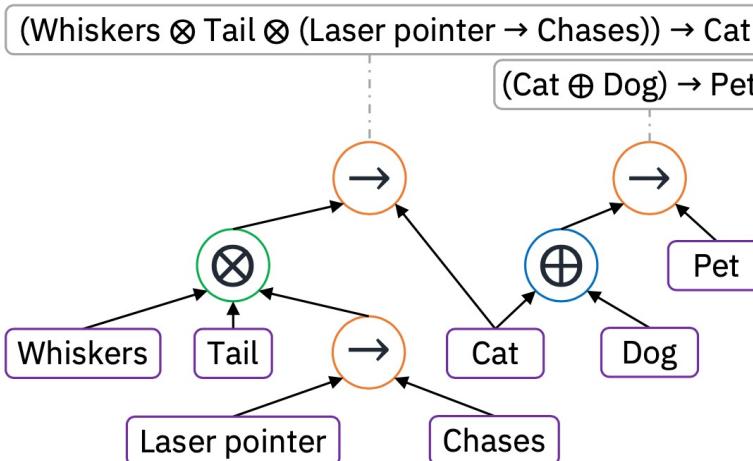


Step 3: Our view for Neuro-Symbolic AI **Challenges and Opportunities**

Selected Neuro-Symbolic AI Models

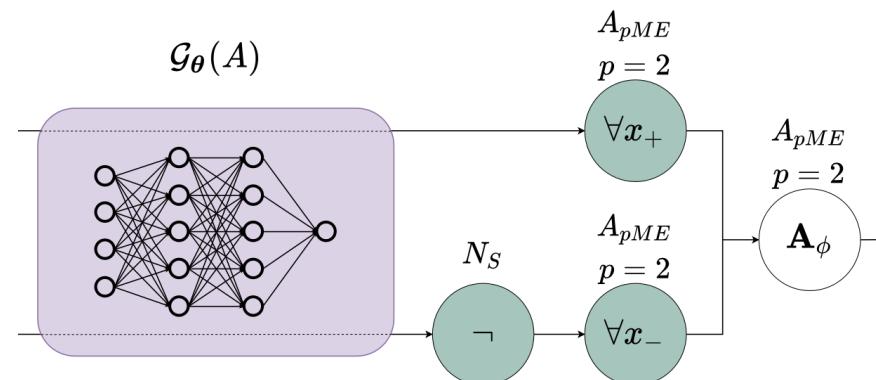
- Logical Neural Network

Neuro:Symbolic->Neuro



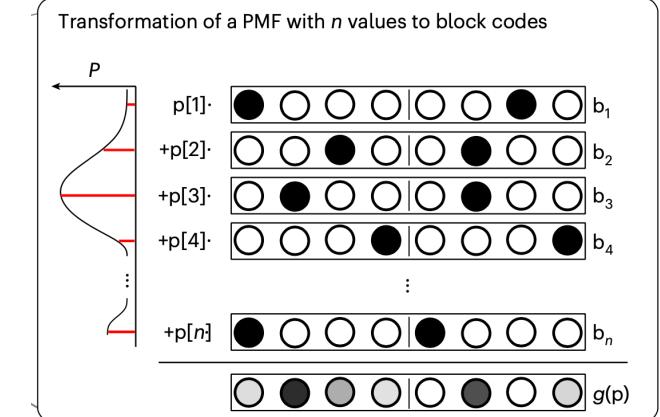
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Neuro[Symbolic]

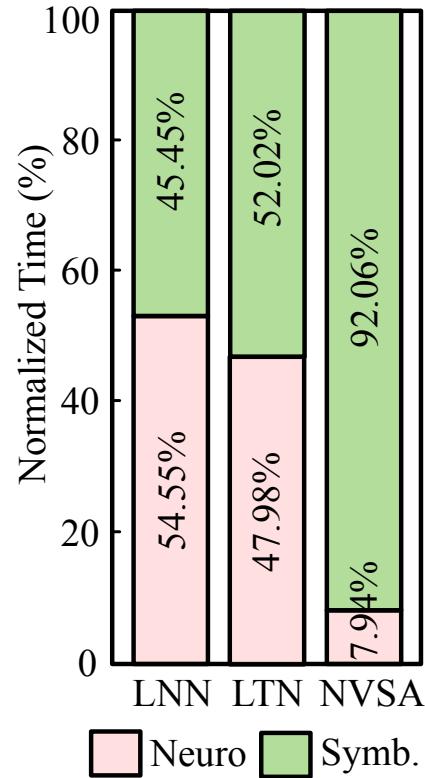


- Neuro-Vector-Symbolic Architecture

Neuro | Symbolic



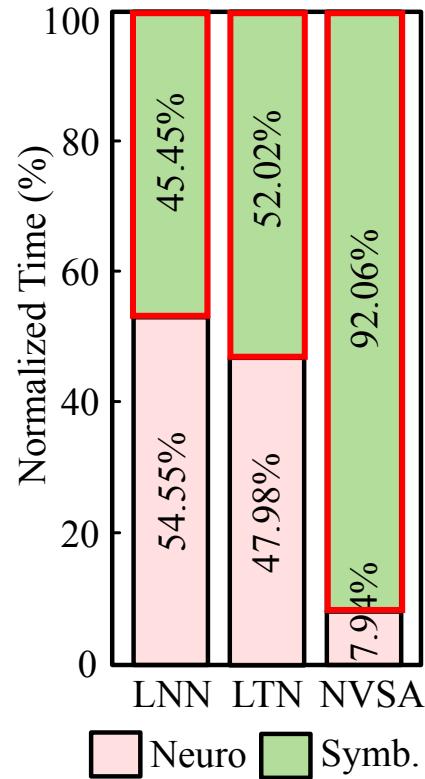
Compute Runtime Analysis



LNN: Logical Neural Network
LTN: Logical Tensor Network
NVSA: Neuro-vector-symbolic architecture

- Measurement Method: Pytorch Profiler
- Hardware: Intel Xeon 4114 CPU, Nvidia RTX 2080 Ti GPU

Compute Runtime Analysis



- Observations
 - **Runtime Breakdown**: symbolic workloads are not negligible and may become a system bottleneck.

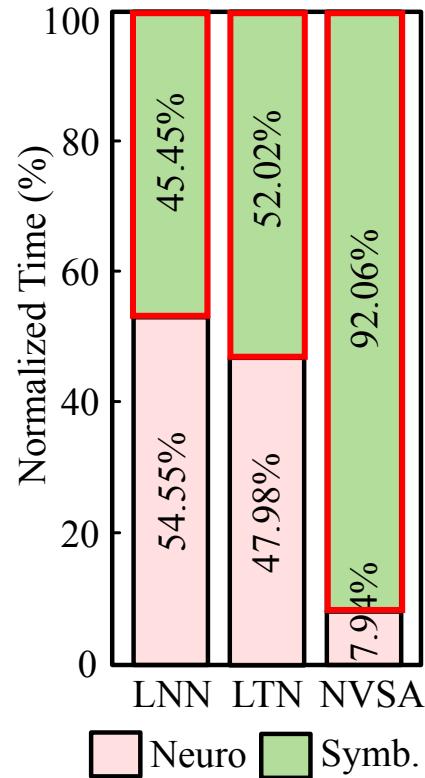
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 - **Runtime Breakdown:** for same test size, neuro vs. symbolic runtime ratio remains stable.

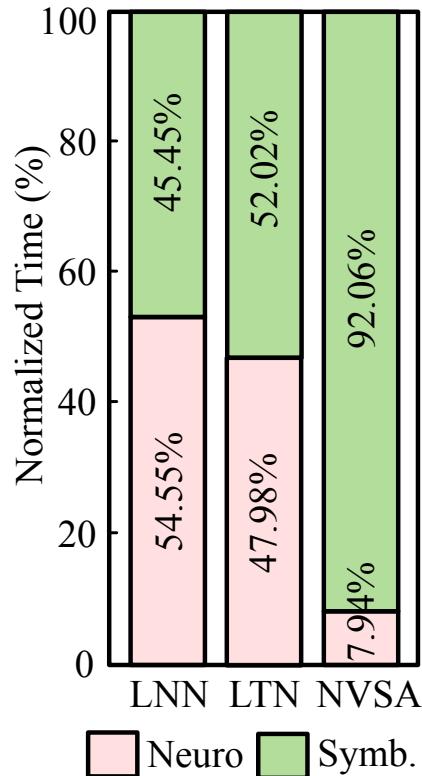
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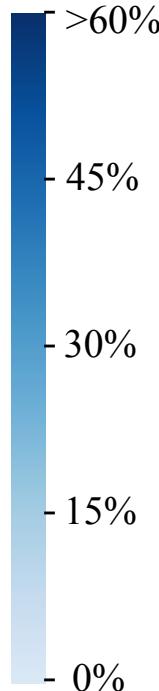
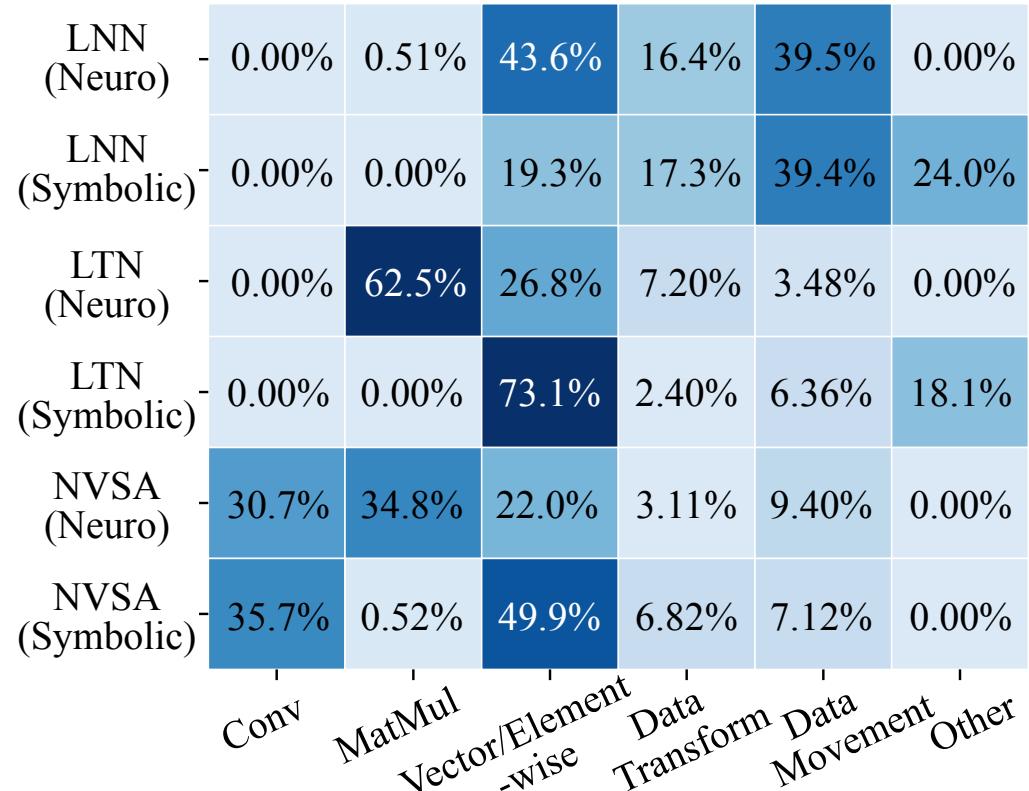
- Observations
 - **Runtime Breakdown:** symbolic workloads are not negligible and may become a system bottleneck.
 - **Runtime Breakdown:** for same test size, neuro vs. symbolic runtime ratio remains stable.
 - **Runtime Scalability:** when test size increase from 2 to 3, runtime increase 5.02x.
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LNN: Logical Neural Network

LTN: Logical Tensor Network

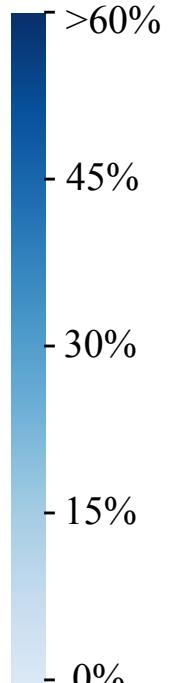
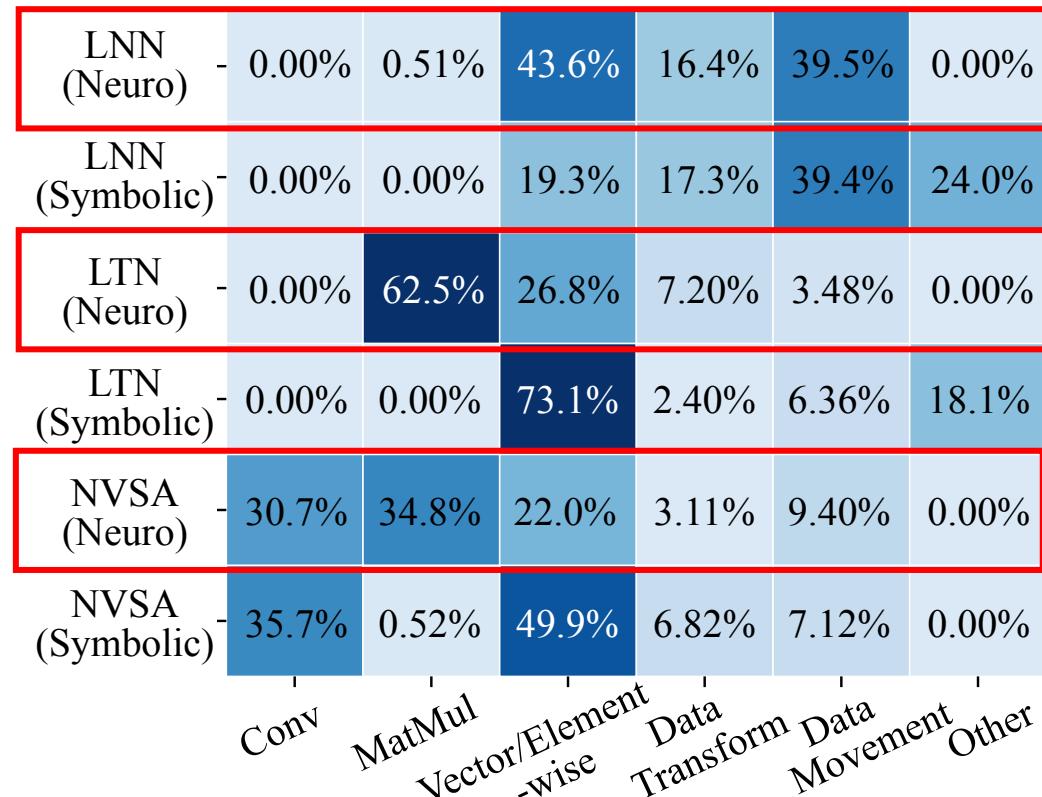
NVSA: Neuro-vector-symbolic architecture

Compute Operator Analysis



- **Six operators:** convolution, matrix multiplication (MatMul), vector/element-wise operation, data transformation, data movement, others (logic)

Compute Operator Analysis

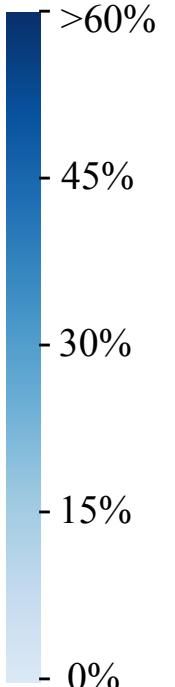
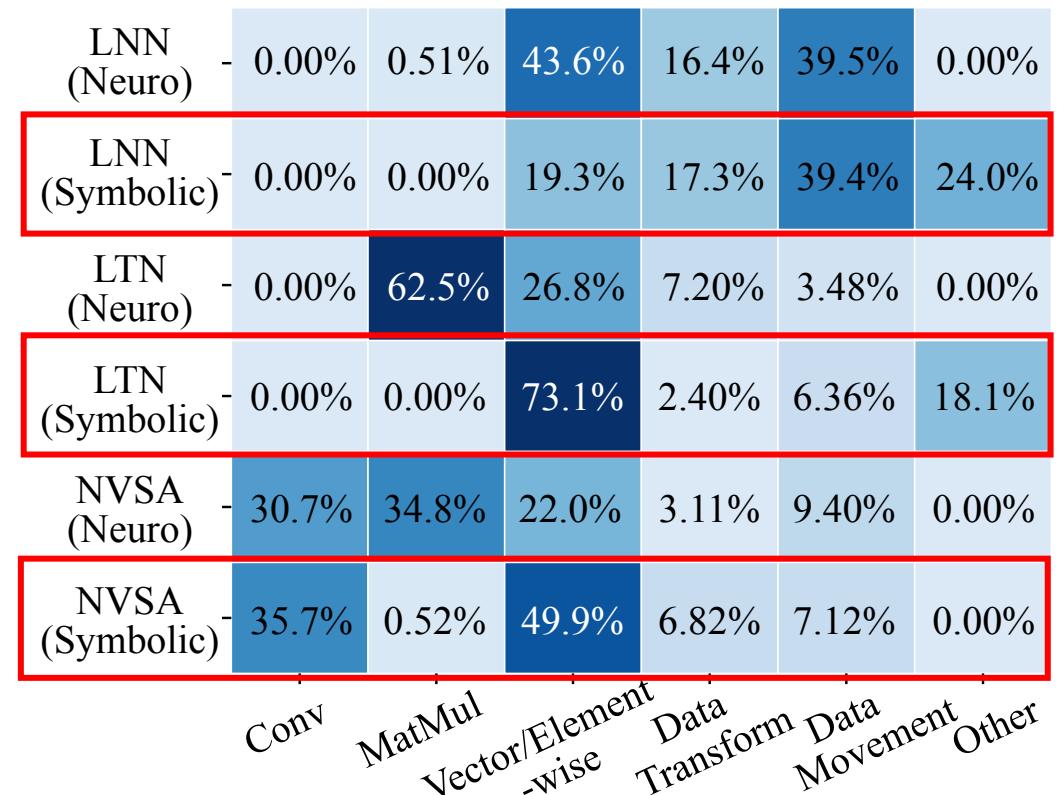


- Observations

- **Neuro Workload:** dominated by MatMul and activation operations

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Compute Operator Analysis

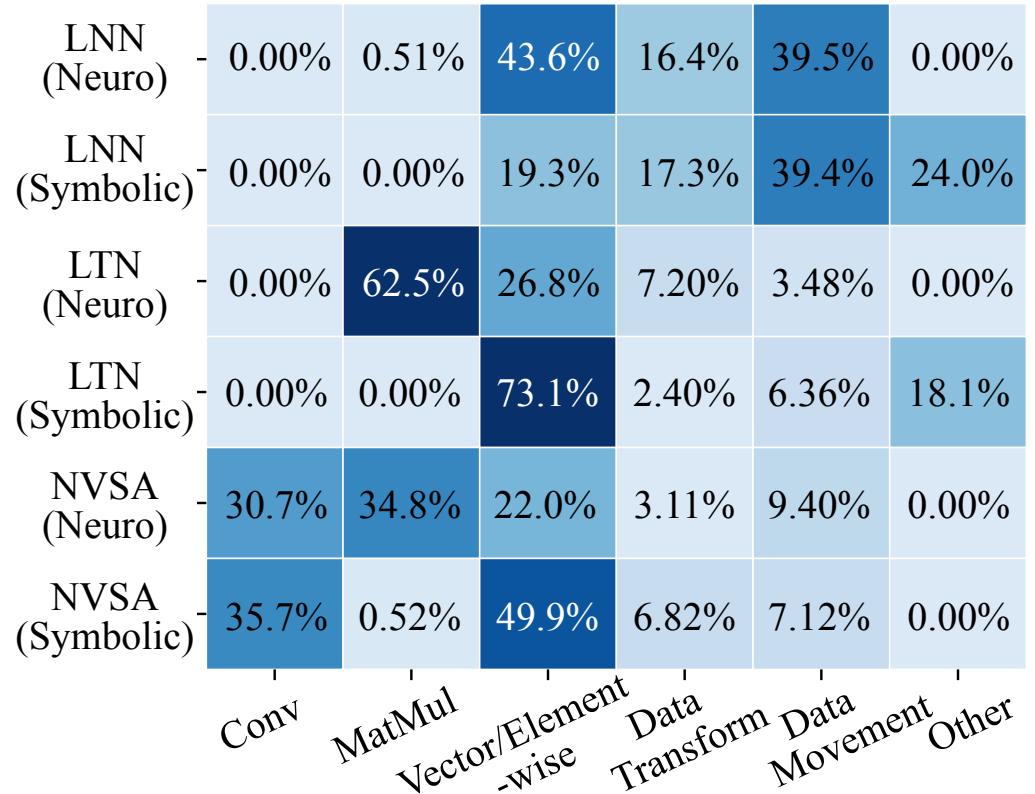


- Observations

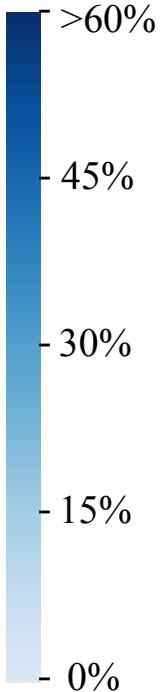
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- **Symbolic Workload:** dominated by vector and scalar operations - low operational intensity and complex control flows (inefficient on GPUs)

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- **Six operators:** convolution, matrix multiplication (MatMul), vector/element-wise operation, data transformation, data movement, others (logic)



• Observations

- **Neuro Workload:** dominated by MatMul and activation operations
- **Symbolic Workload:** dominated by vector and scalar operations - low operational intensity and complex control flows (inefficient on GPUs)
- **Accelerating computation** becomes important

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Step 1: Categorizing Neuro-Symbolic AI **Algorithm**



Step 2: Benchmarking selecting algorithms on current **Hardware**



Step 3: Our view for Neuro-Symbolic AI Challenges and Opportunities

Challenge and Opportunity

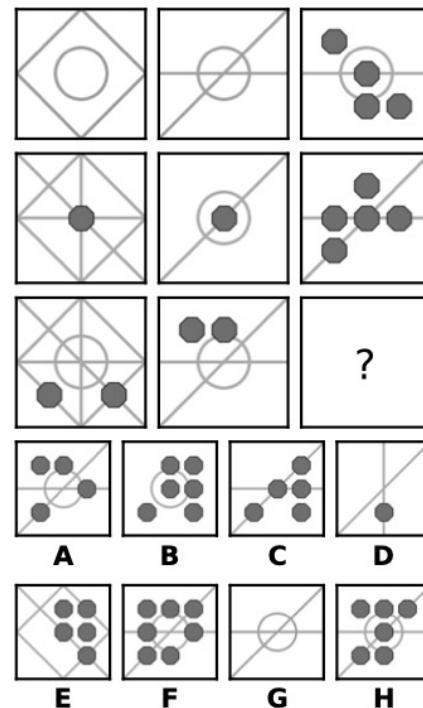
Data



Lack of cognitive datasets



CLEVRER Dataset



RAVEN Dataset

Challenge and Opportunity

Data



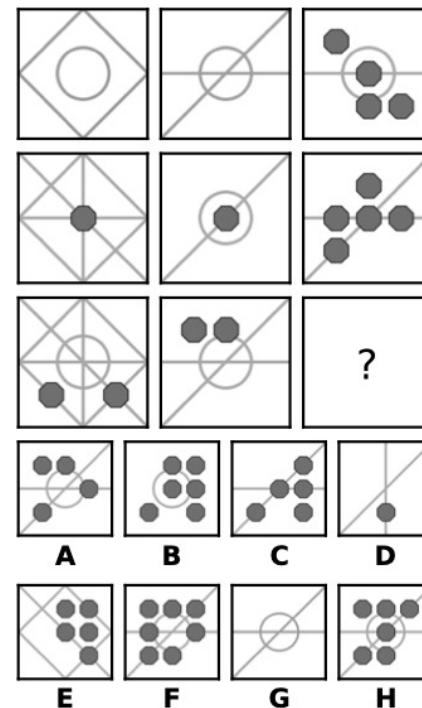
Lack of cognitive datasets



CLEVRER Dataset



Building ImageNet-like NSAI datasets



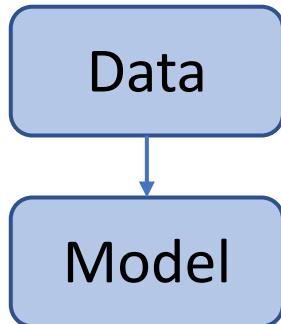
RAVEN Dataset



Human-like AI

Metacognition
Interpretability
Deductive Reasoning
Systematicity
Compositionality
Counterfactual thinking
...

Challenge and Opportunity



Lack of cognitive datasets



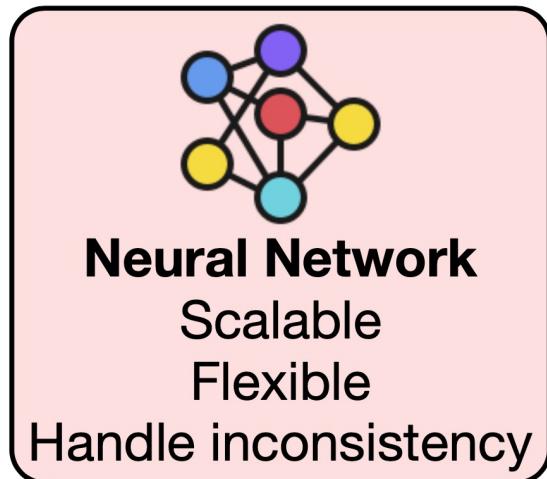
Building ImageNet-like NSAI datasets



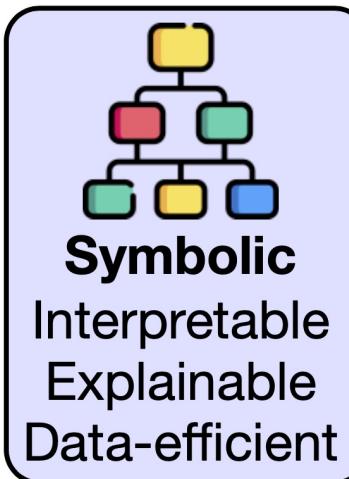
Nascent integration



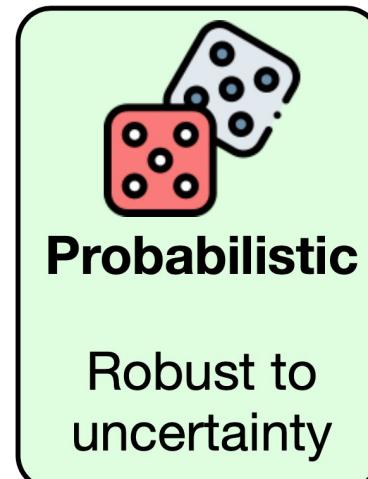
Unifying neuro-symbolic-prob models



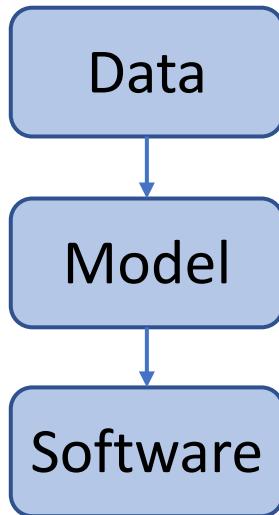
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Challenge and Opportunity



Lack of cognitive datasets



Building ImageNet-like NSAI datasets



Nascent integration



Unifying neuro-symbolic-prob models



Modularity & extensibility



Developing efficient SW framework

Underlying Operations	Examples
Fuzzy logic (LTN)	$F = \forall x(isCarnivor(s)) \rightarrow (isMammal(x))$ $\{isCarnivor(s):[0, 1], isMammal(x):[1, 0]\} \rightarrow F = [1, 0]$
Mul and Add (NVSA)	$X_i \in \{+1, -1\}^d \rightarrow (X_i \cdot X_j)/(X_i + X_j)$
Pre-defined objects (NSVQA)	<code>equal_color: (entry, entry) → Boolean</code> <code>equal_integer: (number, number) → Boolean</code>

Efficient NSAI Software



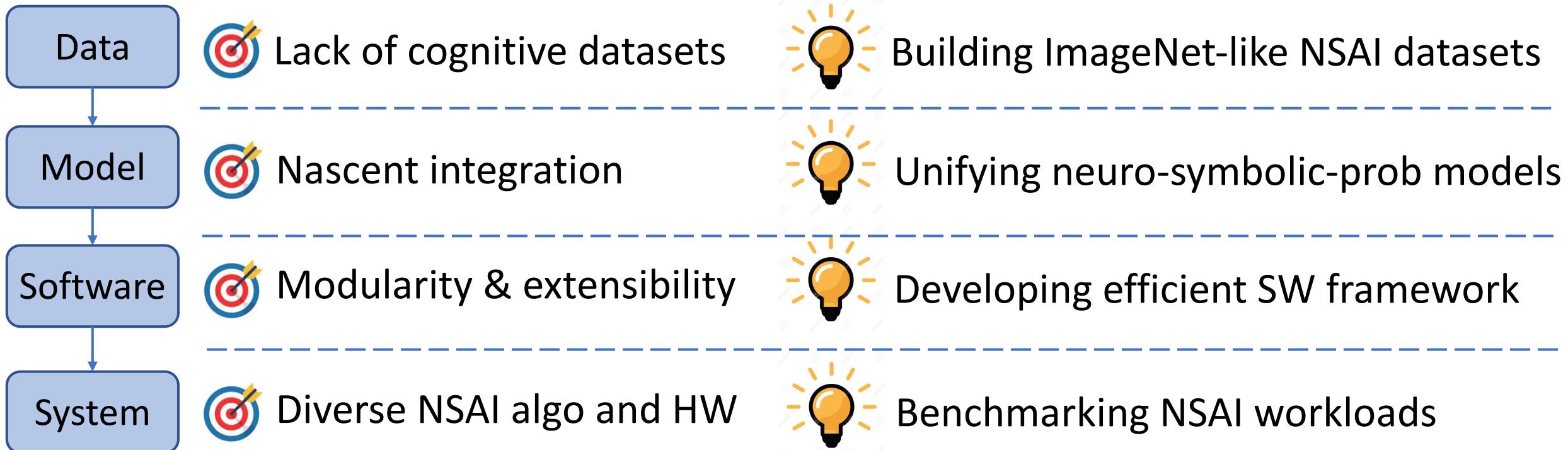
Encompass broad set of reasoning logics

Fast

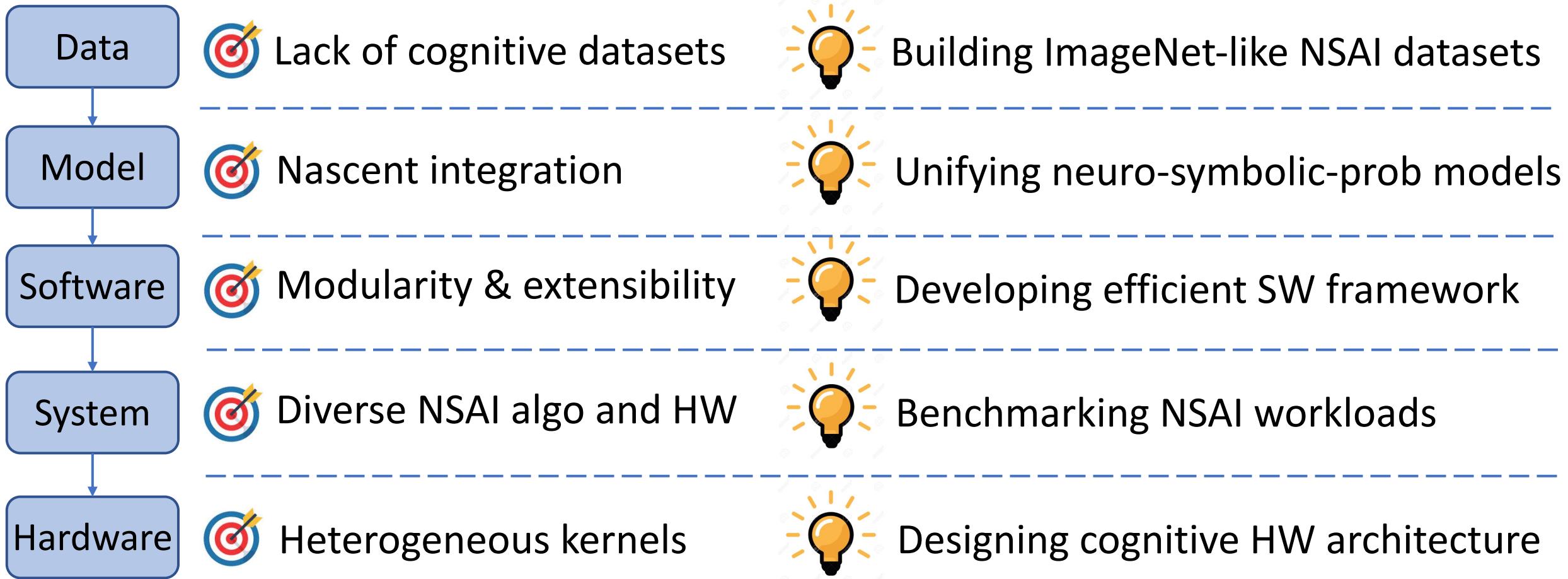
Memory-efficient

...

Challenge and Opportunity



Challenge and Opportunity



Towards Understanding the Computational Characteristics of Neuro-Symbolic Workloads

- Very little understanding exists of the computational characteristics of neuro-symbolic AI workloads

- ✓ Step 1: Categorizing Neuro-Symbolic AI **Algorithm**
- ✓ Step 2: Benchmarking selecting algorithms on current **Hardware**
- ✓ Step 3: Our view for Neuro-Symbolic AI **Challenges and Opportunities**



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Paper available at <https://arxiv.org/pdf/2401.01040.pdf>