An Insect-Inspired Randomly, Weighted Neural Network with Random Fourier Features For Neuro-Symbolic Relational Learning

Jinyung Hong and Theodore P. Pavlic

Arizona State University, Tempe AZ, USA

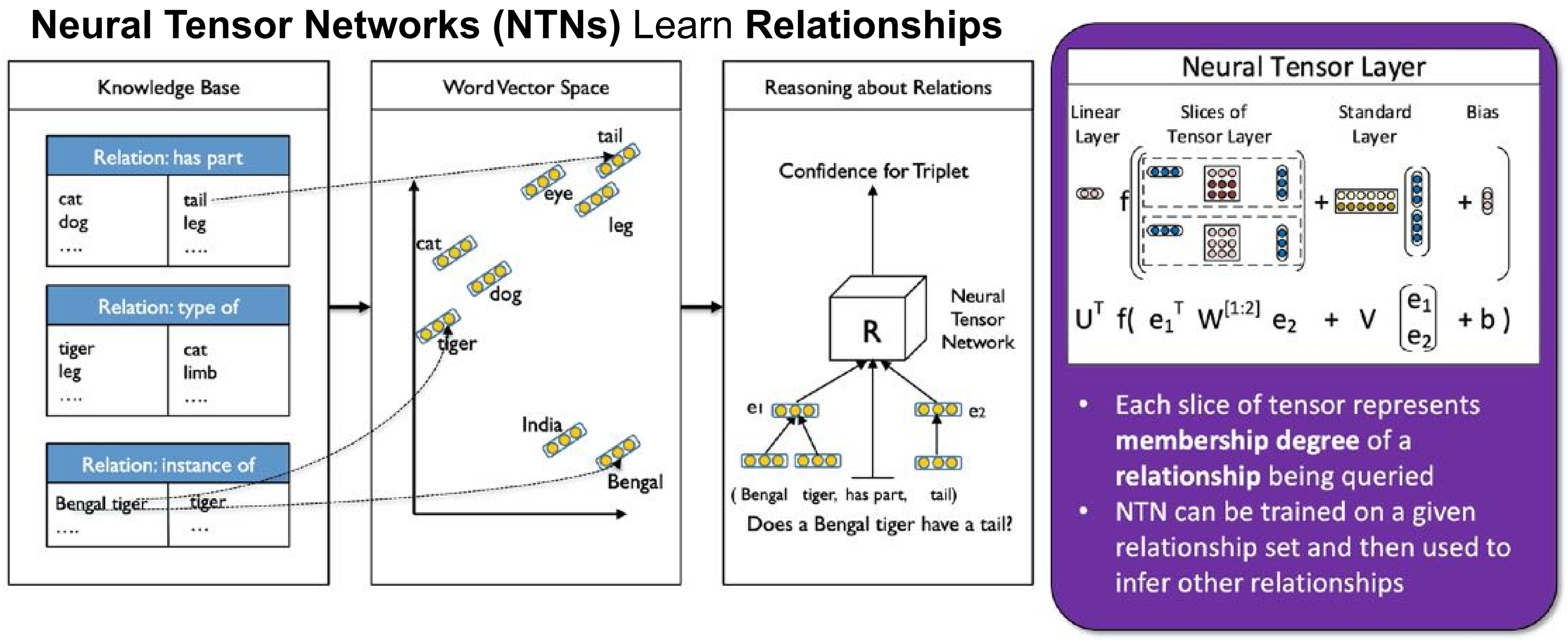
Arizona State University

SEADS Lab

Science & Engineering of Autonomous Decision-making Systems

MOTIVATION

Neural Tensor Networks (NTNs) Learn **Relationships**



Logic Tensor Networks (LTNs)

NTN's can be generalized to learn and reason over **knowledge** that can be represented as predicates in **First-Order Logic.**

For example) $friend(Mary, John)$

Individuals are grounded with real features (e.g. vectors, matrices, ...).

e.g. $\mathcal{G}(Mary) = [6.2, 1.5, \dots] \in \mathbb{R}^m$

Predicates are grounded with operations (e.g. neural networks, ...) that project in the interval [0,1].
The output denotes a *satisfaction level*.

e.g. $\mathcal{G}(friend) : \mathbb{R}^m \times \mathbb{R}^m \longrightarrow [0,1]$

$$\forall x(friend(John, x) \rightarrow friend(Mary, x))$$

Connectives ($\wedge, \vee, \rightarrow, \neg$) are interpreted using fuzzy semantics

e.g. $0.7 \wedge_{\text{prod}} 0.2 = 0.7 \cdot 0.2 = 0.14$

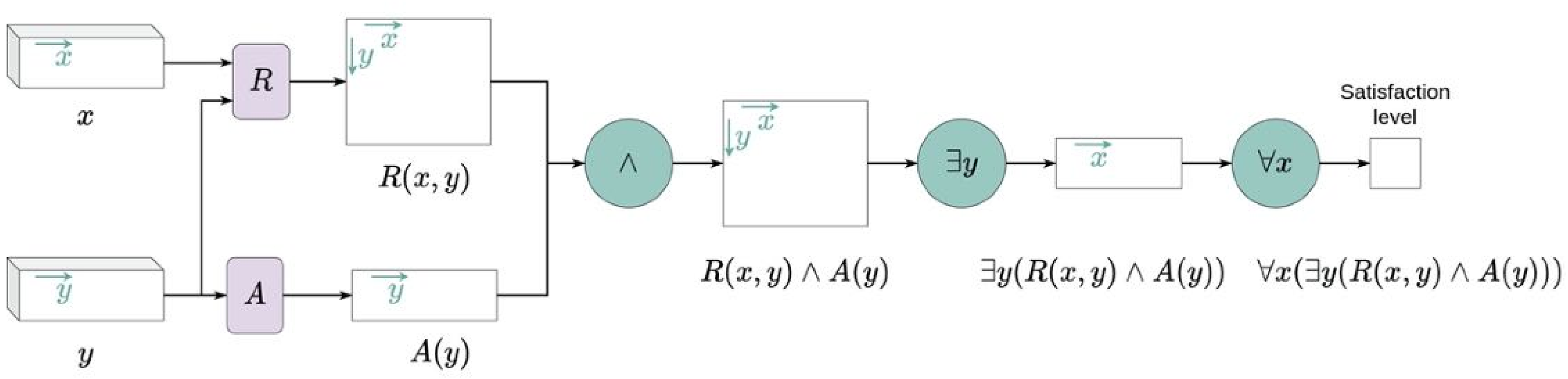
Variables are grounded as a list of n individuals

e.g. $x \in \mathbb{R}^{n \times m}$

Quantifiers ($\forall, \exists$) are interpreted as aggregators

e.g. $\forall_{\text{mean}}(0.7, 0.2, \dots) = \frac{1}{n}(0.7 + 0.2 + \dots)$

e.g. if R denotes the predicate for $friends$, and A denotes the predicate for $Italian$, the following computational graph translates the English sentence "everybody has a friend that is Italian".



EVALUATION

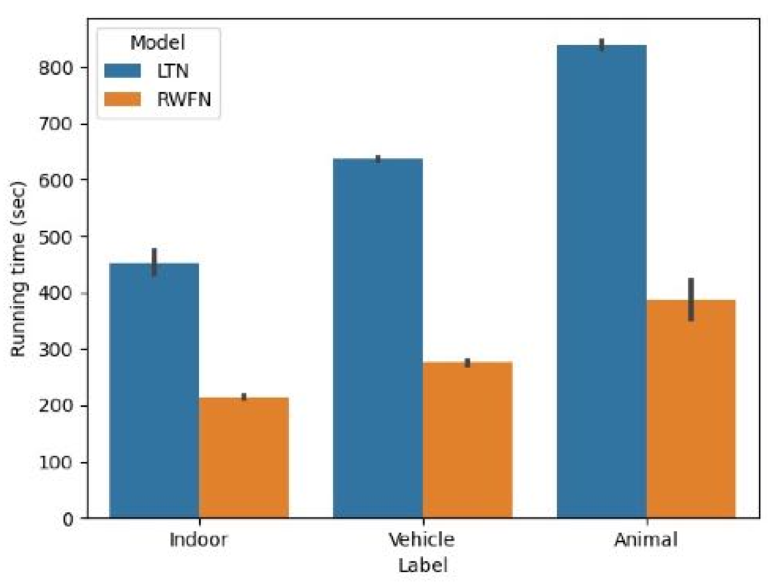
- Semantic Image Interpretation (SII) Tasks
  1. Classification of bounding boxes in an image → Unary Predicate, *Cat*, *Dog*,…
  2. Detection of the *part-of* relation between any two bounding boxes → Binary Predicate, *partOf.*

Table 1

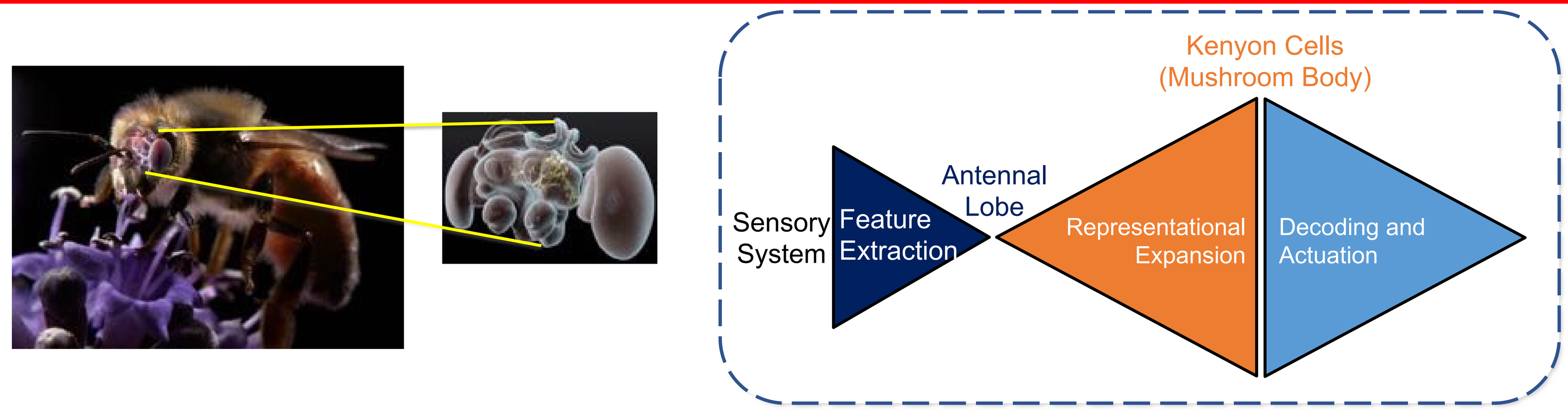
AUC of T1 (object type classification) and T2 (detection of *part-of* relation) for LTN, RWFN, and RWFN with weight sharing across label groups. MEAN$_{\pm 2\times\text{SD}}$ for all models. Best performances shown in **bold**.

Label-Task	LTN	RWFN	RWFN w/ W.S
Indoor-T1	$.769_{\pm.0314}$	$.770_{\pm.0092}$	$\mathbf{.773}_{\pm.028}$
Indoor-T2	$.619_{\pm.082}$	$\mathbf{.648}_{\pm.0621}$	
Vehicle-T1	$.709_{\pm.0289}$	$\mathbf{.711}_{\pm.0162}$	$.706_{\pm.0111}$
Vehicle-T2	$.576_{\pm.0355}$	$\mathbf{.613}_{\pm.0489}$	—
Animal-T1	$\mathbf{.701}_{\pm.024}$	$.700_{\pm.024}$	$.697_{\pm.0237}$
Animal-T2	$.640_{\pm.0783}$	$\mathbf{.661}_{\pm.0364}$	—

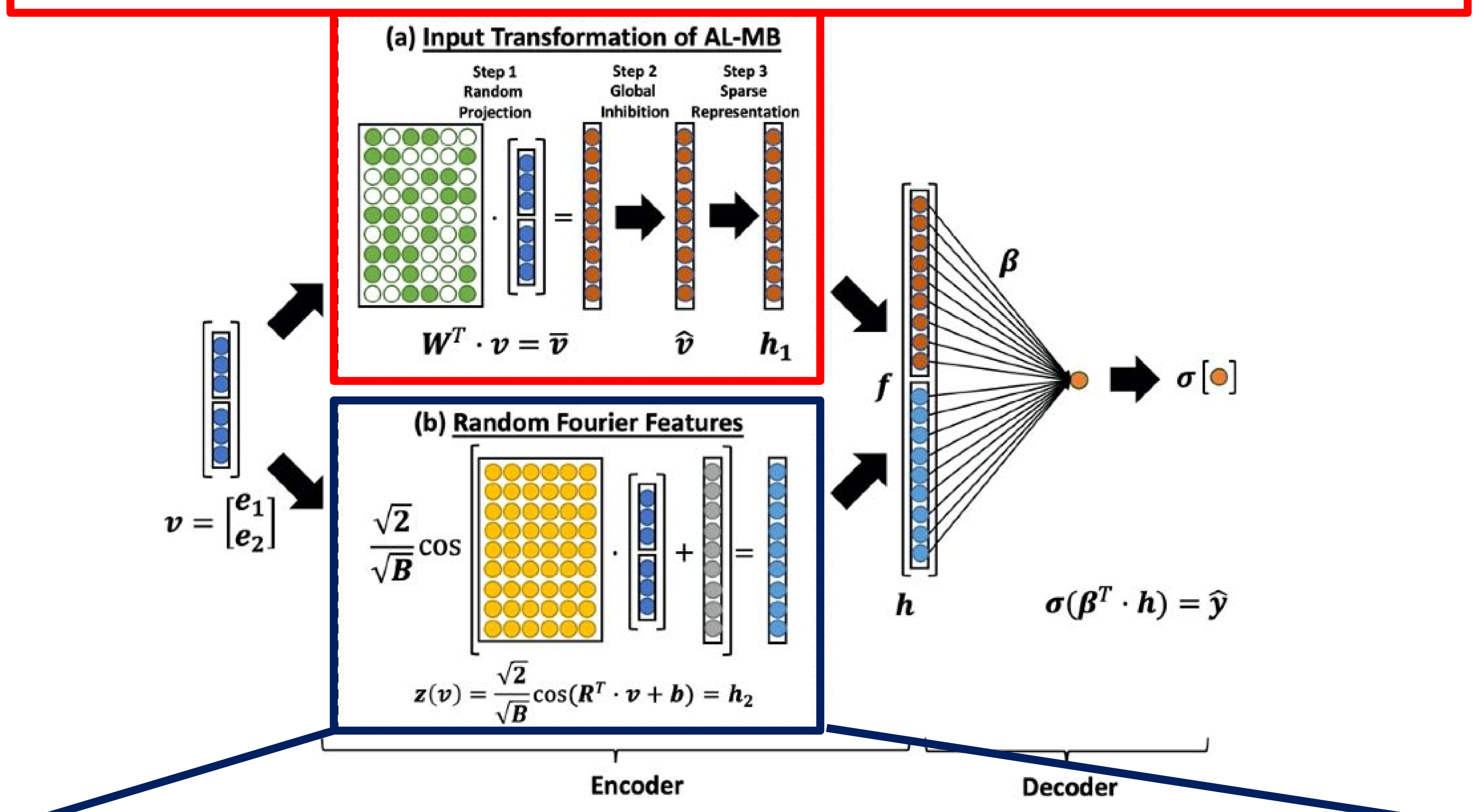
- The Ratio of Total Number of Learnable Parameters between RWFNs and LTNs: **$400 : 24{,}972 \approx 1 : 62$**
- Space Complexity between RWFNs and RWFNs with Weight Sharing: **$O(i \cdot B \cdot n) : O(B \cdot n)$ for SII tasks.**
- Comparison of Running Time between LTNs and RWTNs



RANDOM WEIGHTED FEATURE NETWORK (RWFN)



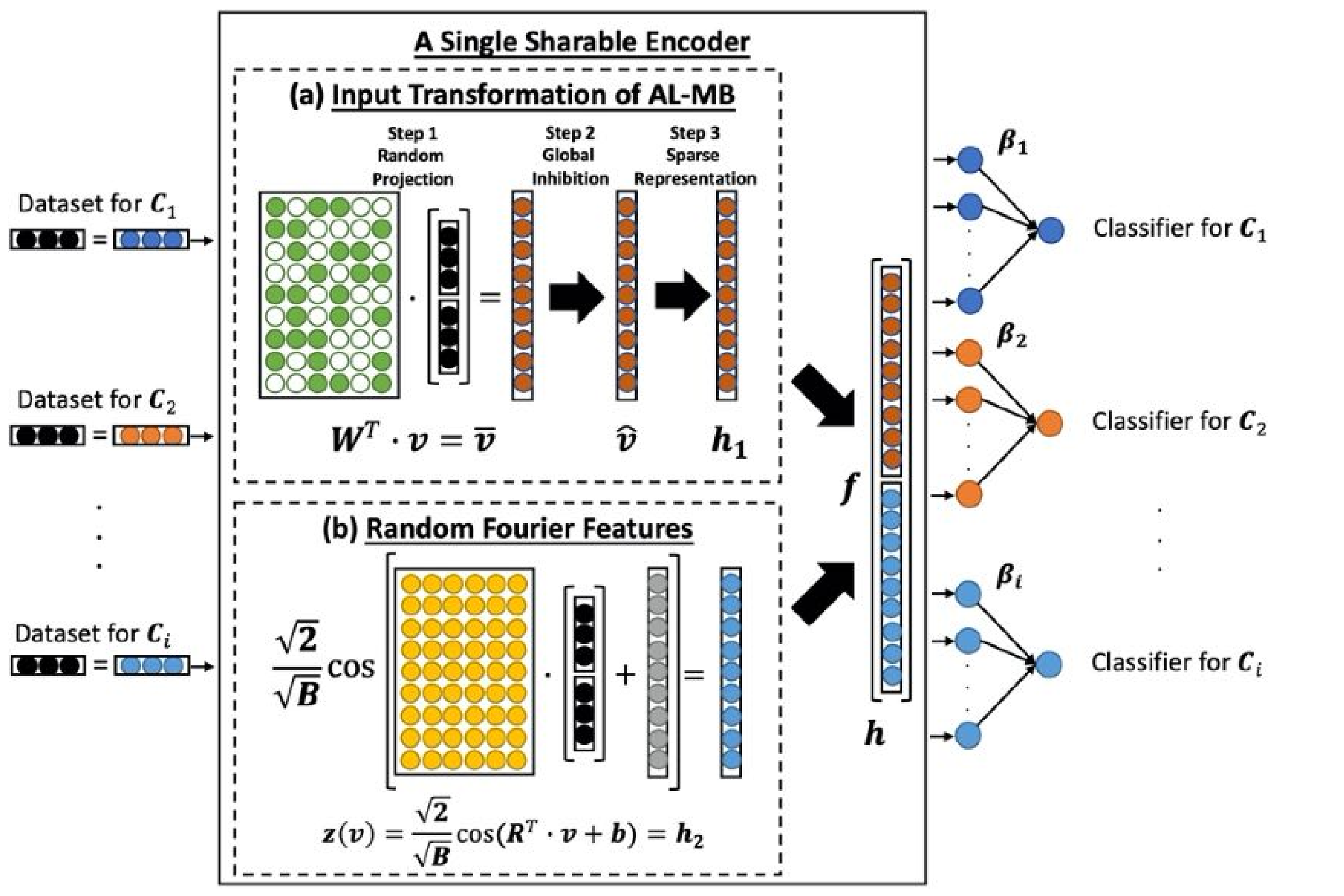
- Stingless bees, derived with respect to honeybees, maintain neural investment in both:
  - Antennal lobes (feature extraction)
  - Mushroom bodies (**high-order reasoning**)



$$f(\mathbf{x}) = \sum_{n=1}^{N} \alpha_n k(\mathbf{x}_n, \mathbf{x}) = \sum_{n=1}^{N} \alpha_n \langle \phi(\mathbf{x}_n), \phi(\mathbf{x}) \rangle \approx \sum_{n=1}^{N} \alpha_n \mathbf{z}(\mathbf{x}_n)^\top \mathbf{z}(\mathbf{x}) = \beta^\top \mathbf{z}(\mathbf{x})$$

- A Randomized feature mapping $\mathbf{z}: \mathbb{R}^d \rightarrow \mathbb{R}^D (D \gg d)$ is defined as Gaussian Kernel Approximation: Learn **non-linear relationship** between entities

RWFN WITH WEIGHT SHARING



CONTRIBUTION

- To the best of our knowledge, our work is the first research to integrate both insect neuroscience and neuro-symbolic approaches for reasoning under uncertainty and for learning in the presence of data and rich knowledge.
- RWFNs achieve better or similar performance despite the faster learning process compared to traditional neural networks due to their special structural characteristics.
- RWFNs provide a new economical way to reduce the space complexity that was not in the existing method because its encoder part can be shared with other predicates.

REFERENCES

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