

Combining Symbolic Expressions and Black-box Function Evaluations in Neural Programs

Forough Arabshahi^{*} Sameer Singh^{*} Animashree Anandkumar[†]

^{*}University of California, Irvine [†]California Institute of Technology

Neural Programming

- Learning black-box functions
- Observations:
 - black-box function evaluations (*fEval*)
 - program execution traces (*eTrace*)
- Challenges: Lack of generalization due to:
 - fEval*: Insufficient structural information
 - eTrace*: Computational issues affecting the domain coverage
- Solution:
 - Most problems have access to symbolic representations (*sym*)
 - Combine *sym* and *fEval* data:
 - sym*: preserve problem's structure
 - fEval*: enable function evaluation

- Case study: Modeling mathematical equations
- Summary of contributions:
 - Combine symbolic representation and function evaluation
 - Equation verification and equation completion using TreeLSTMs
 - Balanced dataset generation method

Mathematical Equation Modeling

- Grammar rules:

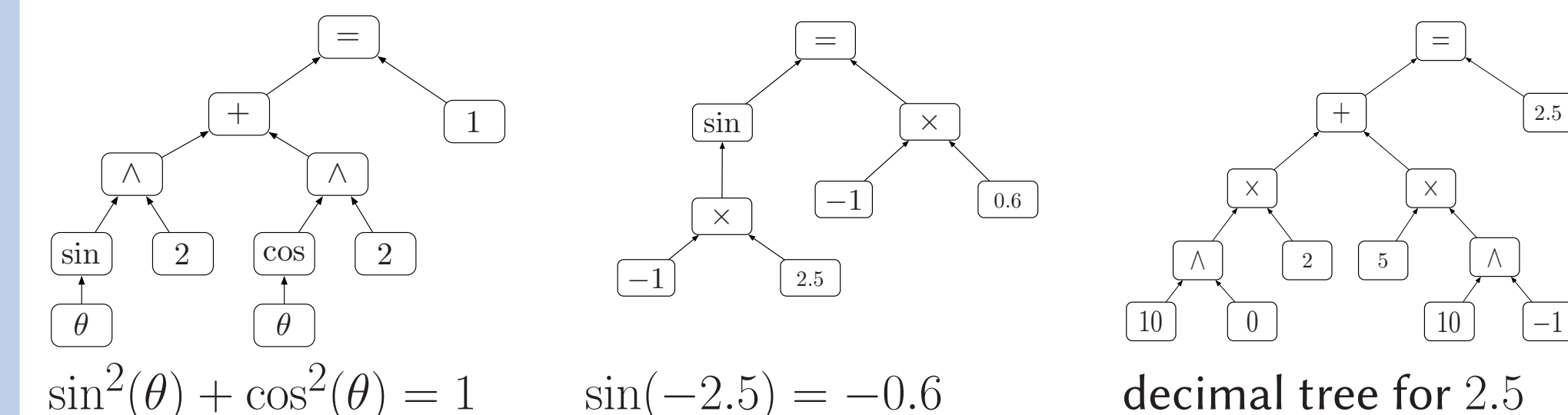
$$\begin{aligned} I &\rightarrow =(E, E), \neq(E, E) \\ E &\rightarrow T, F_1(E), F_2(E, E) \\ F_1 &\rightarrow \sin, \cos, \tan, \dots \\ F_2 &\rightarrow +, \wedge, \times, \dots \\ T &\rightarrow -1, 0, 1, 2, \pi, x, y, \dots, \text{any number in } [-3.14, +3.14] \end{aligned}$$

- Covered domain:

Table: Symbols in our grammar, i.e. the functions, variables, and constants

Unary functions, F_1					Terminal, T		Binary, F_2	
sin	cos	csc	sec	tan	0	1	+	
cot	arcsin	arccos	arcsec	arcsec	2	3	\times	
arctan	arccot	sinh	cosh	csch	4	10	\wedge	
sech	tanh	coth	arsinh	arcosh	0.5	-1		
arsch	arsech	artanh	arcoth	exp	0.4	0.7		
					π	x		

- Examples of equation trees:



Dataset Generation Scheme:

Generating Symbolic Equations

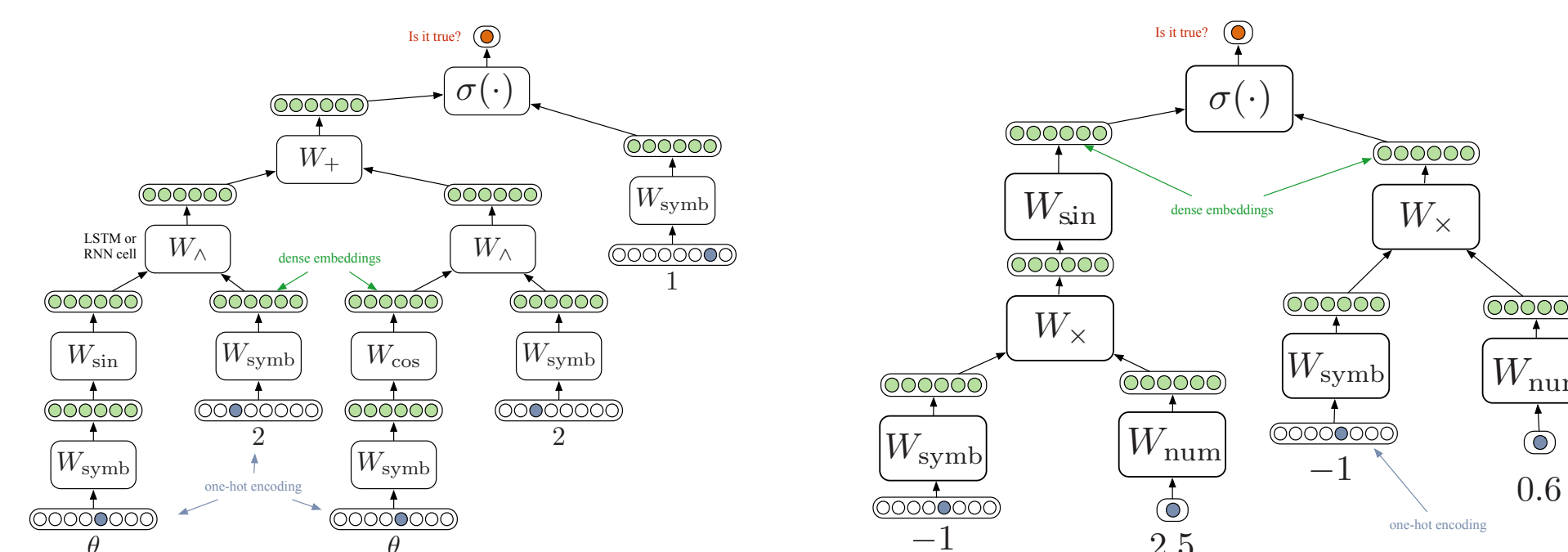
- Generate possible equations **valid** in the grammar
 - Start from a small initial set of axioms
 - For each axiom, choose a random tree node
 - Make local random changes to the node:
 - Problem: More incorrect equations than correct
 - Solution: **Sub-tree matching**
- Generate additional **correct** equations
 - mathDictionary*: A dictionary of valid mathematical statements.
 - E.g. $(x + y : y + x)$ forms a **key-value** pair
 - For each correct equation in the dataset, chose a random tree node
 - Find a dictionary **key** whose pattern matches the chosen sub-tree
 - Replace the sub-tree with the **value**'s pattern, e.g:
 - Equation: $\sin^2 \theta + \cos^2 \theta = 1$
 - Chosen node: $+$
 - Key-value pair: $(x + y : y + x)$
 - output: $\cos^2 \theta + \sin^2 \theta = 1$

Generating function evaluation equations

- Function Evaluation
 - Range of floating point numbers of precision 2: $[-3.14, 3.14]$
 - For each unary function: draw a random number and evaluate
 - For each binary function: draw two random numbers and evaluate
- Representation of numbers
 - For all numbers in the dataset, form the decimal tree expansion
 - E.g. $2.5 = 2 \times 10^0 + 5 \times 10^{-1}$

Tree LSTMs for Modeling Equations

- Tree LSTM whose structure mirrors the input equation
 - Function** blocks are LSTM cells
 - Weight sharing between occurrences of the same function
 - Symbol** block is a 1-layer feed-forward net for embedding terminals
 - Number** block is a 2-layer feed-forward net for embedding numbers



- Baselines:

- Sequential Recurrent Neural Networks
- Sequential LSTMs
- Tree-structured RNNs without function evaluation data
- Tree-LSTMs without function evaluation data
- Tree-structured RNNs with function evaluation data

Experiments and Results

Complexity of an equation: its expression tree depth

- Equation Verification: Generalization to unseen identities

Table: **Generalization Evaluation**: the train and the test contain equations of the same depth [1,2,3,4]. Results are on unseen equations. *Sym* and *F Eval* refer to accuracy on Symbolic and function evaluation expressions, respectively. Test set sizes shown as the counts in (Sym + F Eval) data.

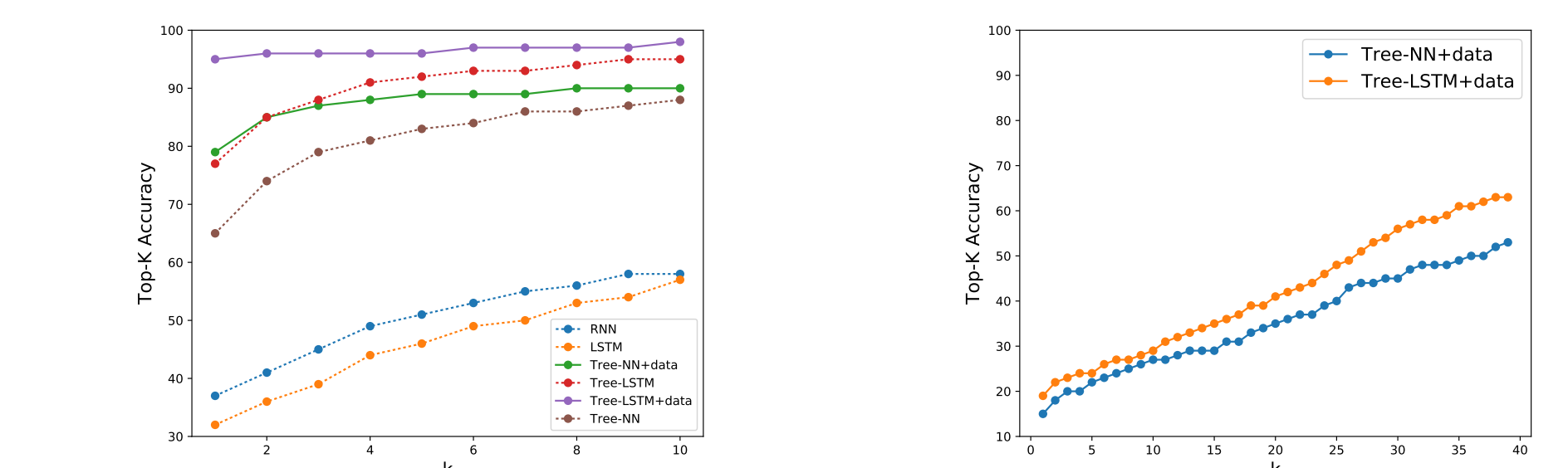
Approach	Sym	F Eval	depth 1	depth 2	depth 3	depth 4
Test set size	3527	401	5+2	542+158	2416+228	563+13
Majority Class	50.24	50.00	20.00	45.75	52.85	43.69
Sympy	81.74	-	80.00	89.11	82.98	69.44
RNN	66.37	-	50	62.93	65.13	72.32
LSTM	81.71	-	80.00	79.49	80.81	83.86
TreeNN	92.06	-	100	95.37	94.16	87.45
TreeLSTM	95.18	-	80.00	96.50	95.07	94.50
TreeNN + data	93.38	92.81	87.5	94.43	92.32	93.58
TreeLSTM + data	97.11	97.17	75.00	98.14	97.01	97.05

- Equation Verification: Extrapolation to unseen depths

Table: **Extrapolation Evaluation** to measure capability of the model to generalize to unseen depth. Acc: Accuracy, Prec: Precision, Rec: Recall

Approach	Train:1,2,3; Test on 4			Train:1,3,4; Test on 2		
	Acc	Prec	Rec	Acc	Prec	Rec
Majority Class	55.22	0	0	56.21	0	0
RNN	65.15	68.61	75.51	71.27	82.98	43.27
LSTM	76.40	71.62	78.35	79.31	75.27	79.31
TreeNN	88.36	87.87	85.86	92.58	89.04	94.71
TreeLSTM	93.27	90.20	95.33	94.78	94.15	93.90
TreeNN + data	92.71	88.07	93.66	94.09	91.06	93.19
TreeLSTM + data	96.17	92.97	97.15	97.37	96.08	96.86

- Equation Completion



$4^{\tanh(0)} = \blacksquare x$	$\tan(\blacksquare) = 0.29$	
-2^0	0.9999	0.28
1^0	0.9999	0.27
7^0	0.9999	0.29
-3^0	0.999	0.26
8^0	0.999	0.25
	0.9977	0.9977
	0.9977	0.9977
	0.9977	0.9977
	0.9977	0.9977
	0.9977	0.9977

