IWLS Programming Contest 2020: Team 3's Report

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Outline

- Problem Description
- Our approach
  - DT-based model
  - NN-based model
  - bagging ensemble
- Experimental results
- Conclusions

PROBLEM DESCRIPTION

Problem Description

- Learn an unknown Boolean function $f: \{0,1\}^n \to \{0,1\}$ from a training dataset consisting of input-output pairs.

- The learned function should be in the form of And-Inverter Graph (AIG) with strict hardware cost ($\leq$ 5000 gates), and will be evaluated by its prediction accuracy in hidden testing dataset.

Benchmarks

- Each benchmark is provided in PLA format and contains 6400 minterms in training, validation and testing set respectively.

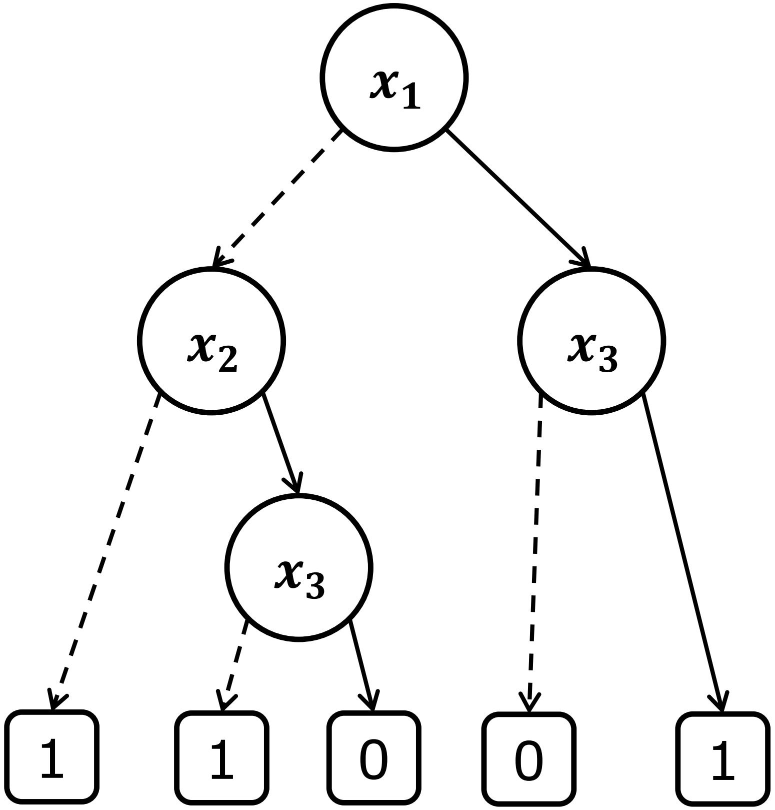
The 100 Functions in our Benchmark Set: Arithmetic, Random Logic, ML

00-09	2 MSBs of k-bit adders for k in {16, 32, 64, 128, 256}
10-19	MSB of k-bit dividers and remainder circuits for k in {16, 32, 64, 128, 256}
20-29	MSB and middle bit of k-bit multipliers for k in {8, 16, 32, 64, 128}
30-39	k-bit comparators with k in {8, 16, ..., 4096}
40-49	LSB and middle bit of k-bit square-rooters with k in {16, 32, 64, 128, 256}
50-59	10 outputs of PicoJava design with 16-200 inputs and roughly balanced on- & offset
60-69	10 outputs of MCNC i10 design with 16-200 inputs and roughly balanced on- & offset
70-79	5 other outputs from MCNC benchmarks + 5 symmetric functions of 16 inputs
80-89	10 binary classification problems from MNIST group comparisons
90-99	10 binary classification problems from CIFAR-10 group comparisons

OUR APPROACH

DT-based Model

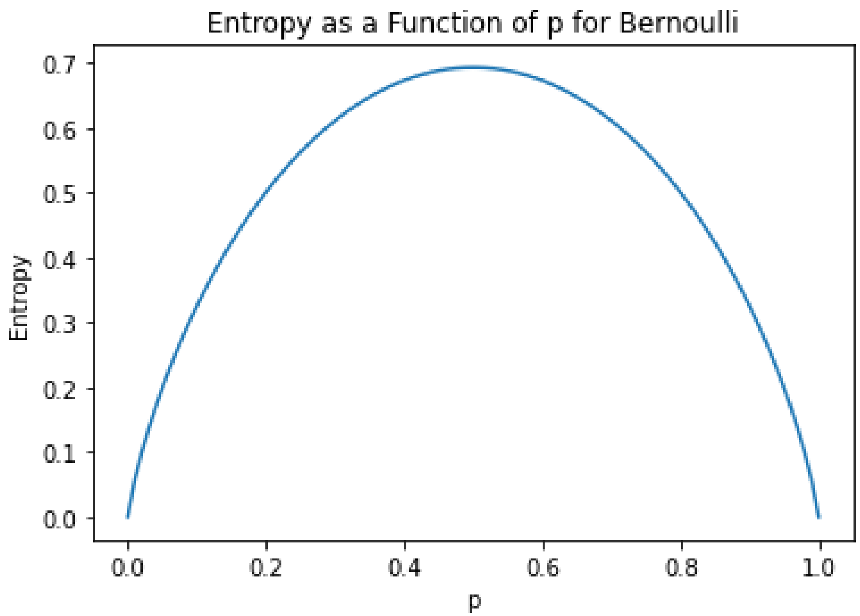
- Binary decision tree



x_1	x_2	x_3	y
0	0	0	1
0	0	1	1
0	1	0	1
0	1	1	0
1	0	0	0
1	0	1	1
1	1	0	0
1	1	1	1

Entropy

- $entropy = -p\log_2 p - (1-p)\log_2(1-p)$,
  where p is the probability of true label ($y = 1$).



When $p = 0 \text{ or } 1$, we have the lowest $entropy = 0 \rightarrow$ no uncertainty.

When $p = 0.5$, we have the maximum $entropy = 1 \rightarrow$ highest uncertainty.

Information Gain

- The branching variable is selected based on maximum information gain.
- Information gain of node n of variable x:

$$E_n - p_0 E_0 - p_1 E_1$$

where E_n is the entropy of n, E_0 is the entropy of the 0-child of n, E_1 is the entropy of the 1-child of n, p_0 and p_1 are the ratio of the data with $x = 0$ and $x = 1$, respectively.

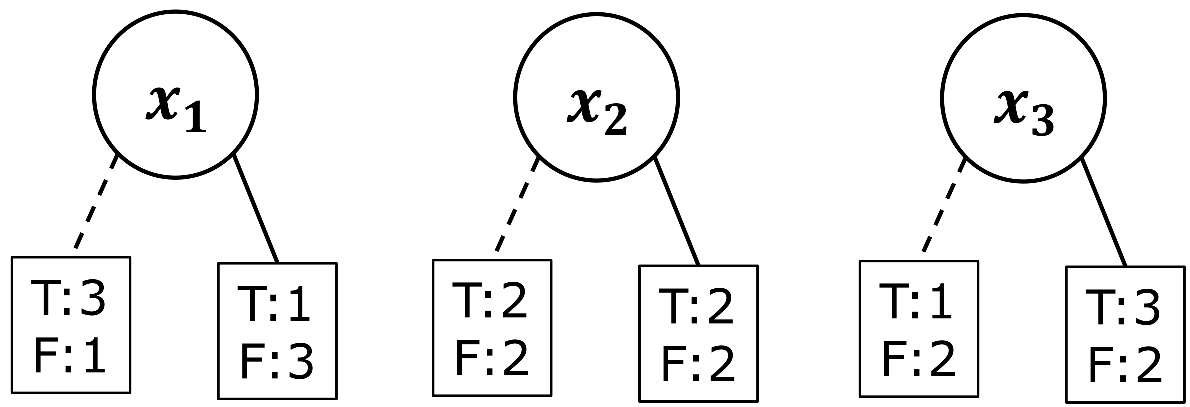
Growing DT

- Choosing the 1st branching variable

example:

x_1	x_2	x_3	y
0	0	0	0
0	0	1	1
0	0	1	1
0	1	1	1
1	0	0	0
1	1	1	0
1	1	1	0
1	1	0	1

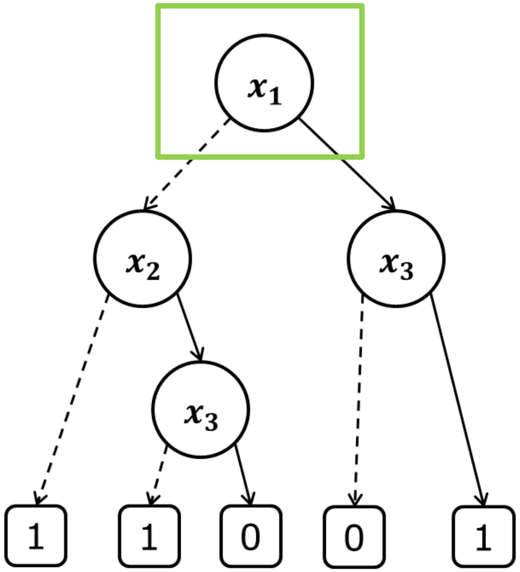
initial entropy: $-\frac{1}{2}\log_2\frac{1}{2}-\frac{1}{2}\log_2\frac{1}{2}=1$



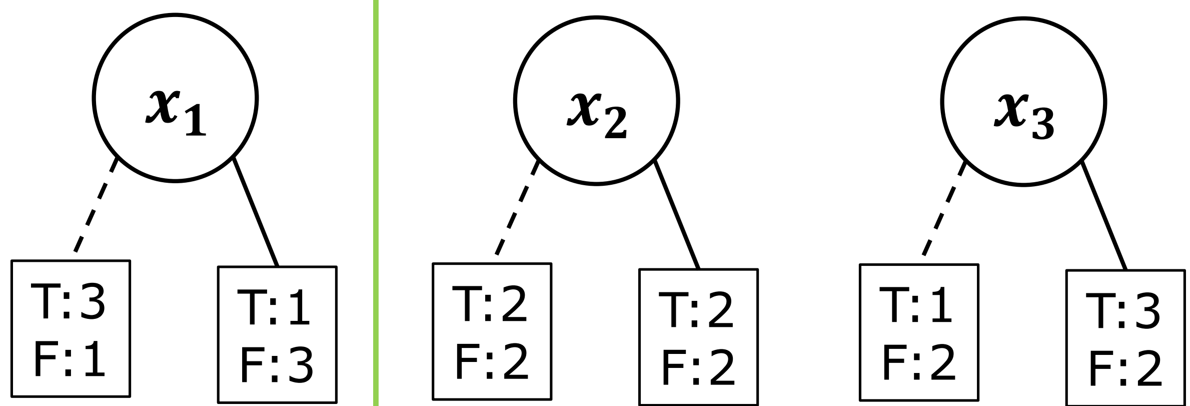
entropy	0.81	0.81	1	1	0.92	0.97
info. Gain	$1-\frac{4}{8}\cdot 0.81+\frac{4}{8}\cdot 0.81=0.19$		$1-\frac{4}{8}\cdot 1-\frac{4}{8}\cdot 1=0$		$1-\frac{3}{8}\cdot 0.92-\frac{5}{8}\cdot 0.97=0.049$	

Growing DT

- Choosing the 1st branching variable



initial entropy: $-\frac{1}{2}\log_2\frac{1}{2}-\frac{1}{2}\log_2\frac{1}{2}=1$

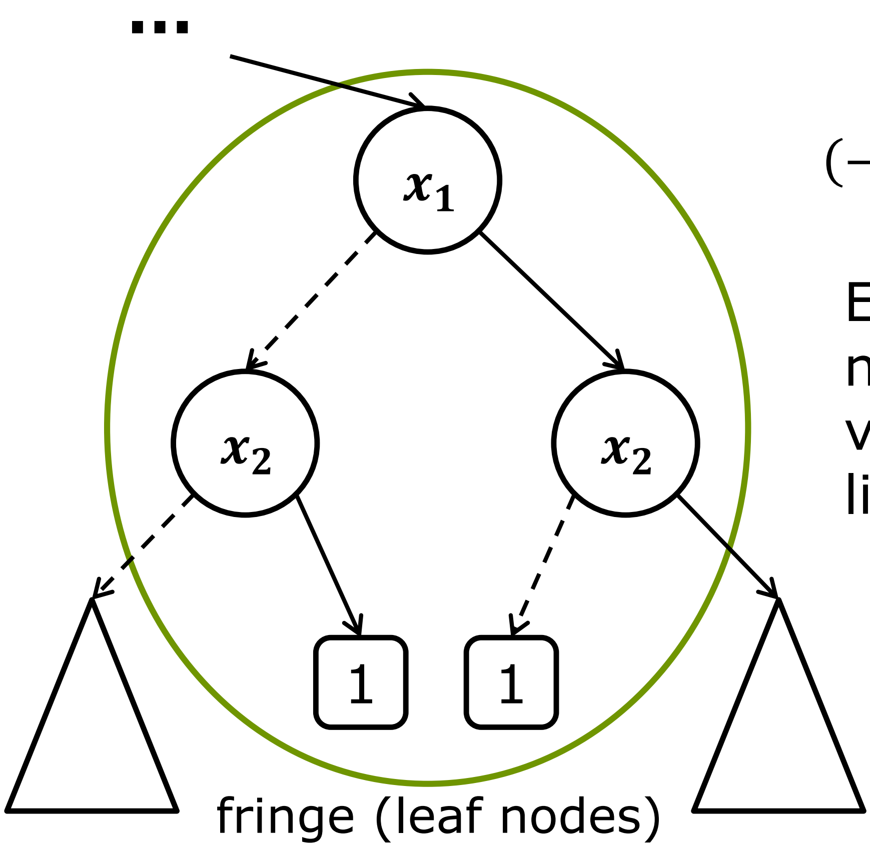


	x_1		x_2		x_3	
entropy	0.81	0.81	1	1	0.92	0.97
info. Gain	$1-\frac{4}{8}\cdot 0.81+\frac{4}{8}\cdot 0.81=0.19$		$1-\frac{4}{8}\cdot 1-\frac{4}{8}\cdot 1=0$		$1-\frac{3}{8}\cdot 0.92-\frac{5}{8}\cdot 0.97=0.049$	

max. gain

DT-based Model

- Fringe-feature extraction [1, 2]

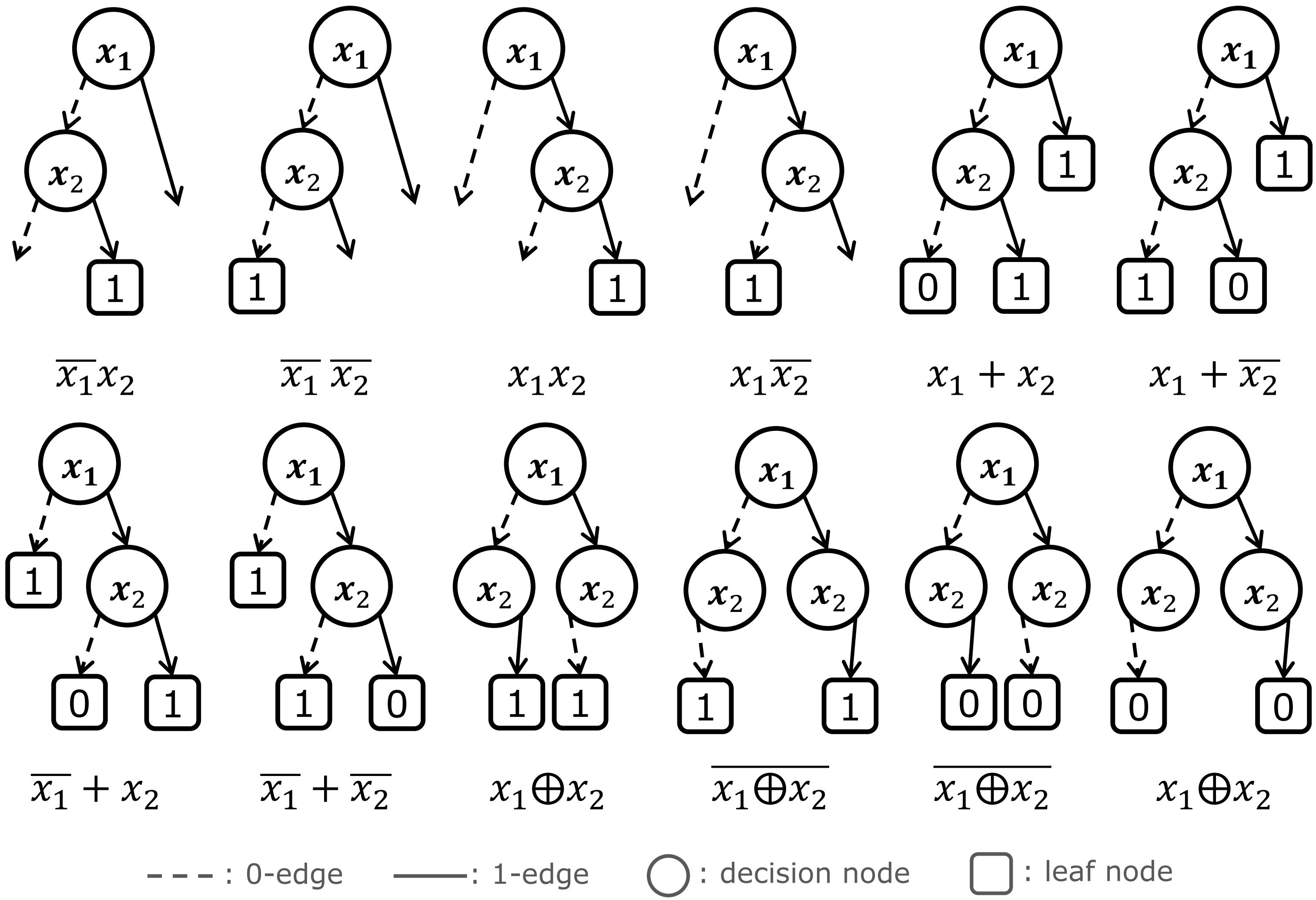


$(\neg x_1 \wedge x_2) \vee (x_1 \wedge \neg x_2) = x_1 \oplus x_2$

Extract $x_{new} = x_1 \oplus x_2$ as the new composite feature of 2 variables, and add it to the list of decision variables.

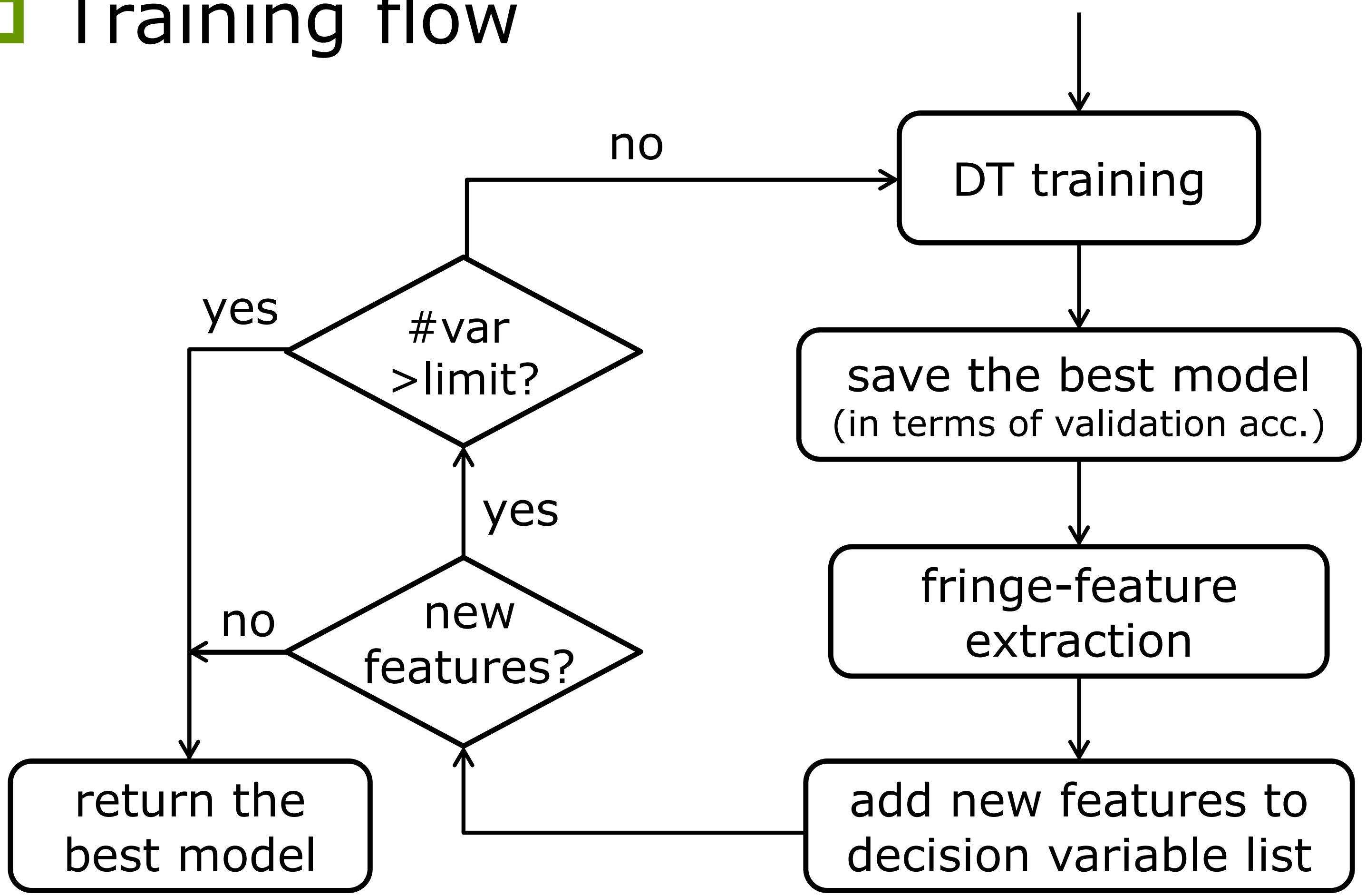
[1] Pagallo et al., 1990. [2] Oliveira et al., 1993.

DT-based Model



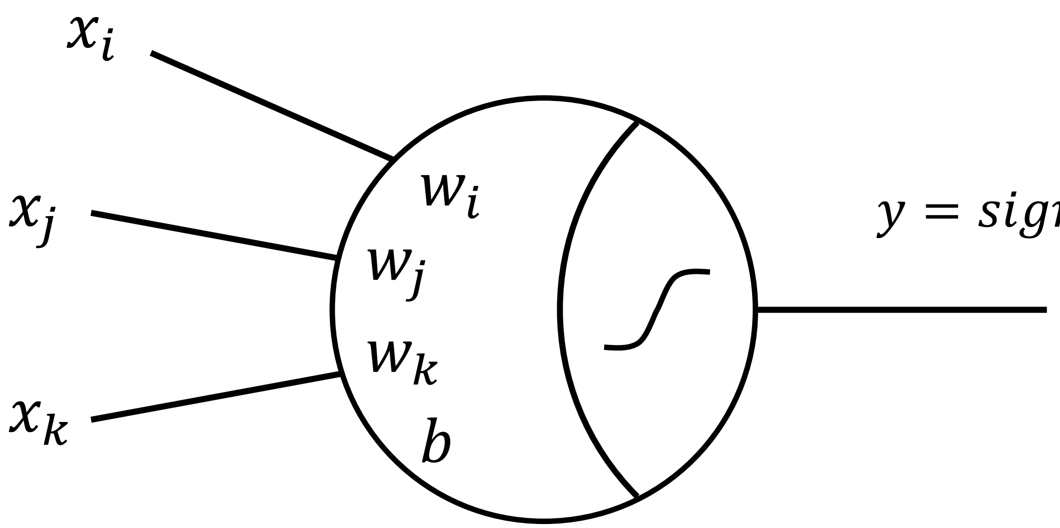
DT-based Model

- Training flow



NN-based Model

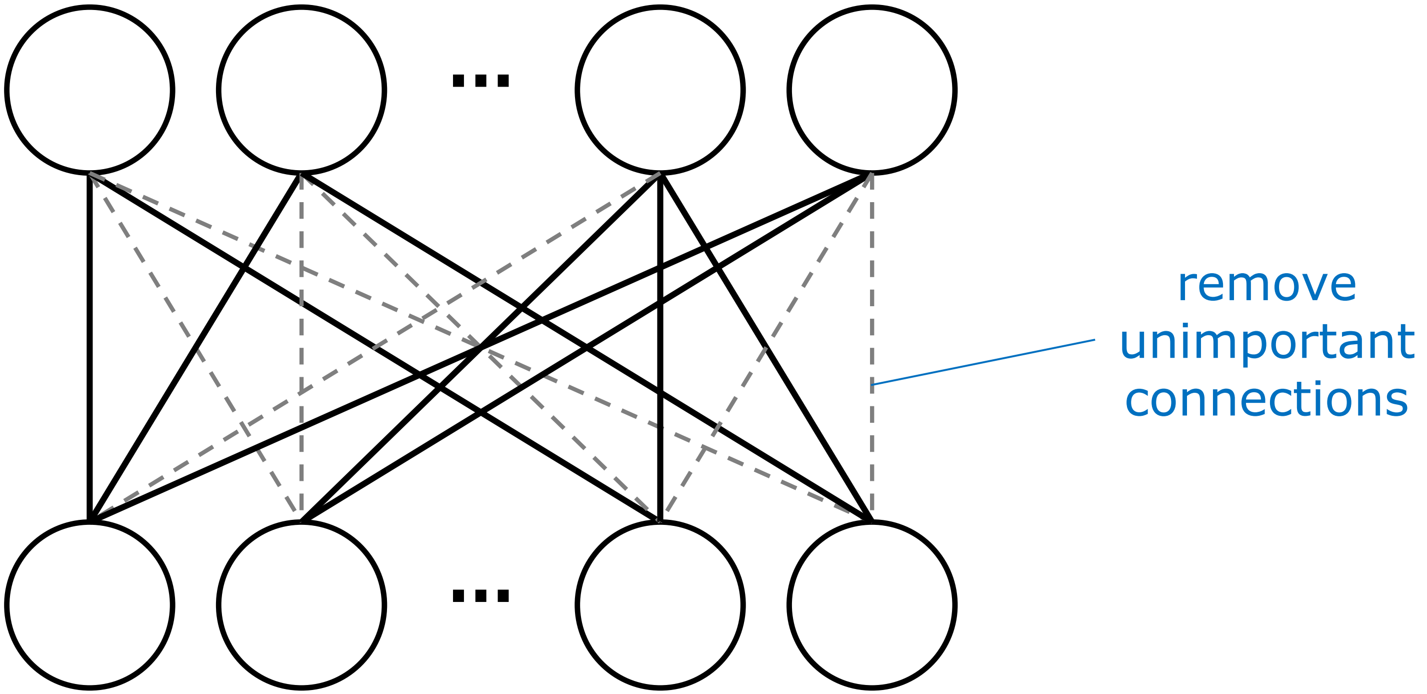
- 3 layer network, each layer is fully-connected and uses sigmoid as the activation function



$$y = sigmoid\left(\sum_i w_i x_i + b\right)$$

NN-based Model

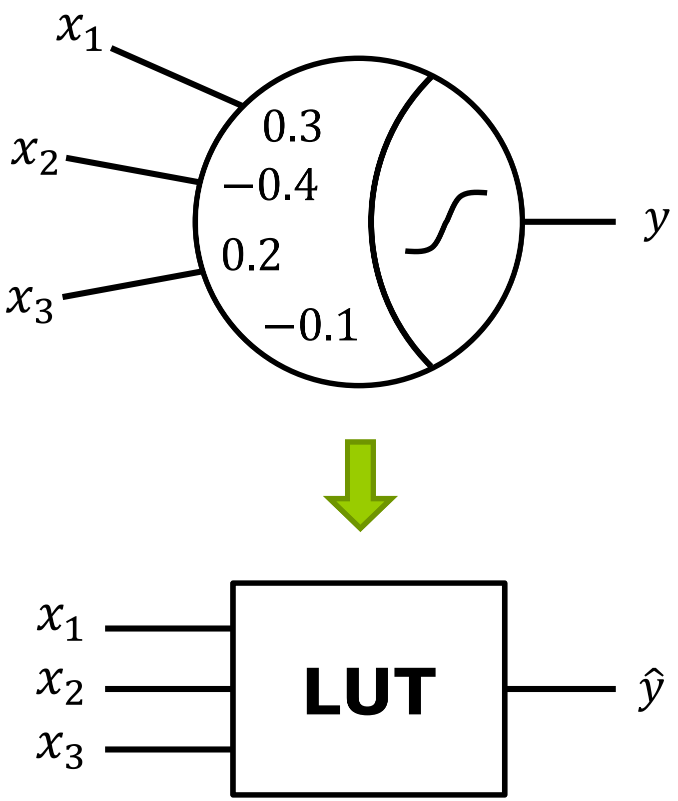
- Connection pruning [3]



[3] Han et al., 2015.

NN-based Model

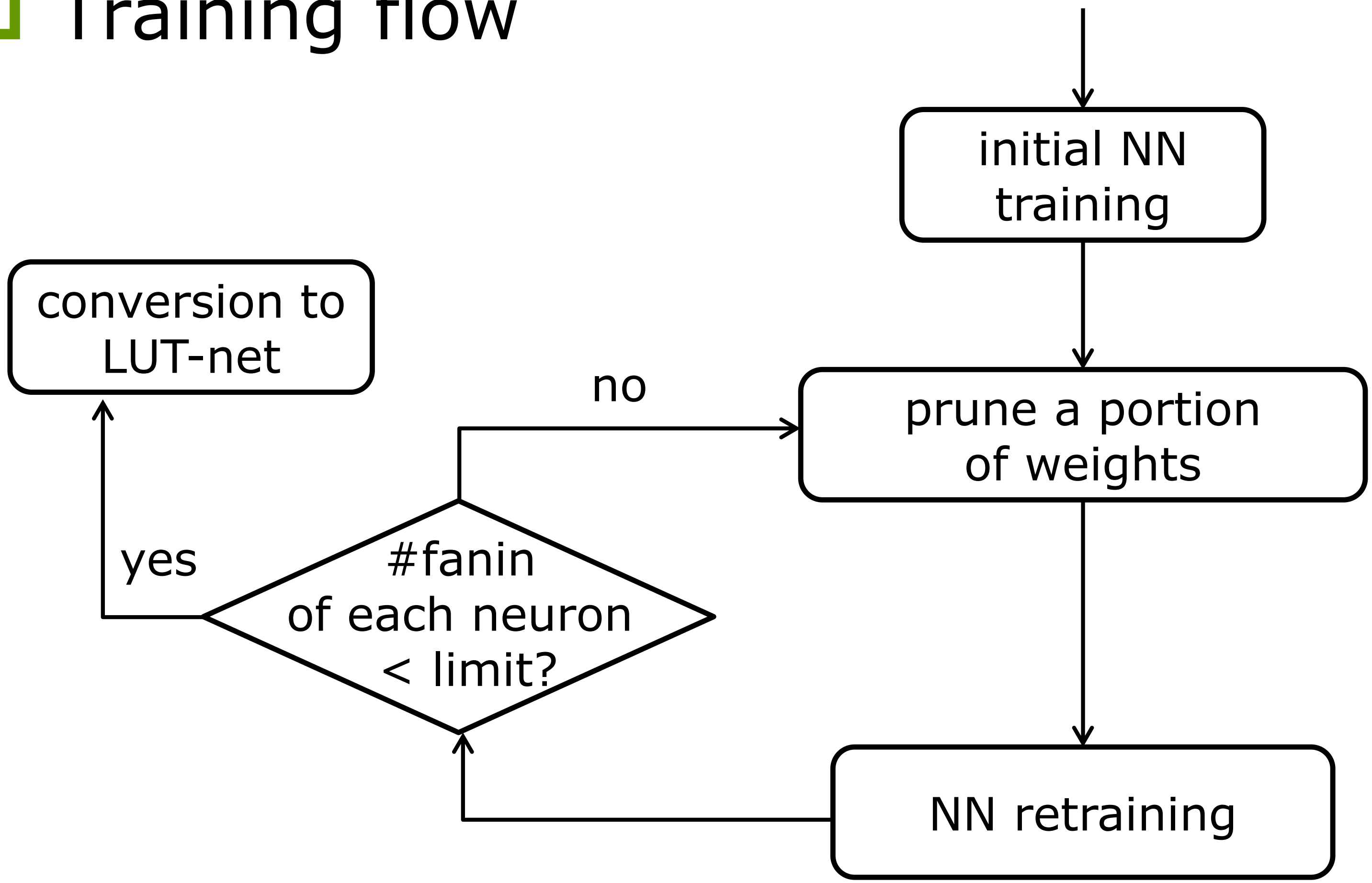
- Convert neurons to LUTs



x_1	x_2	x_3	y	$\hat{y}$
0	0	0	0.48	0
0	0	1	0.52	1
0	1	0	0.38	0
0	1	1	0.43	0
1	0	0	0.55	1
1	0	1	0.60	1
1	1	0	0.45	0
1	1	1	0.50	1

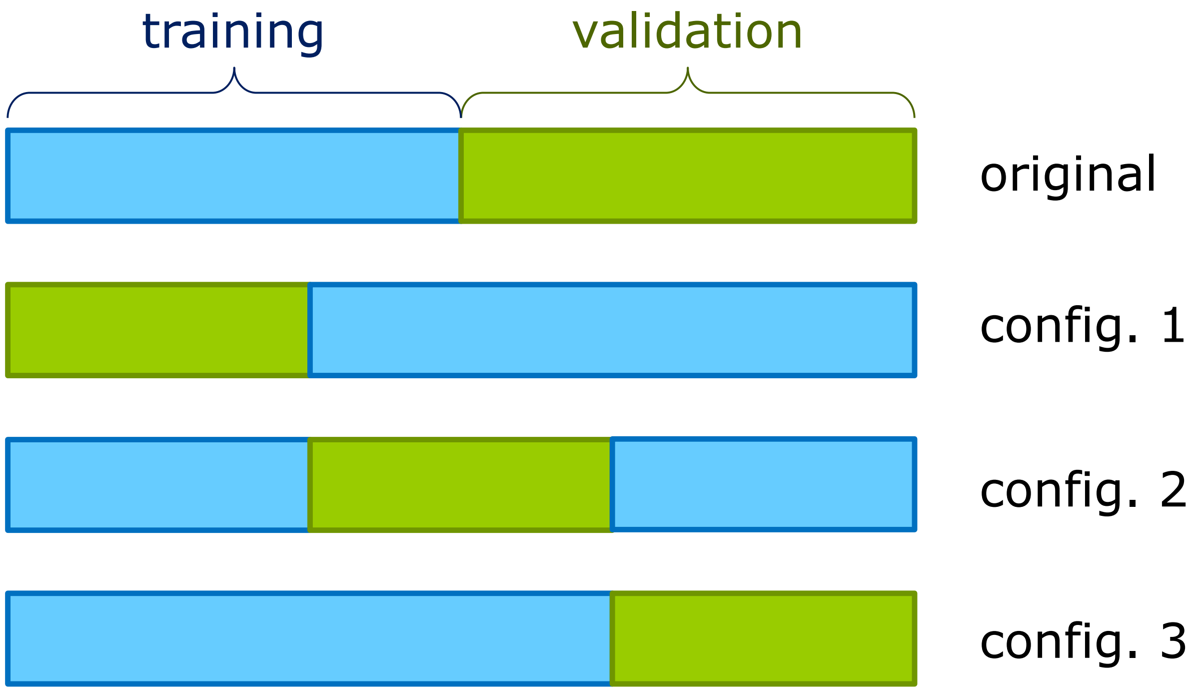
NN-based Model

- Training flow



Bagging Ensemble

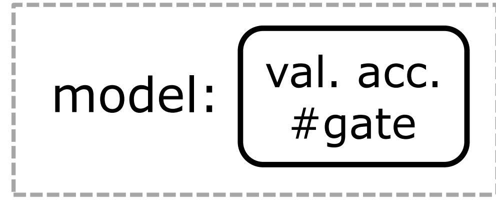
- Re-partitioning the dataset

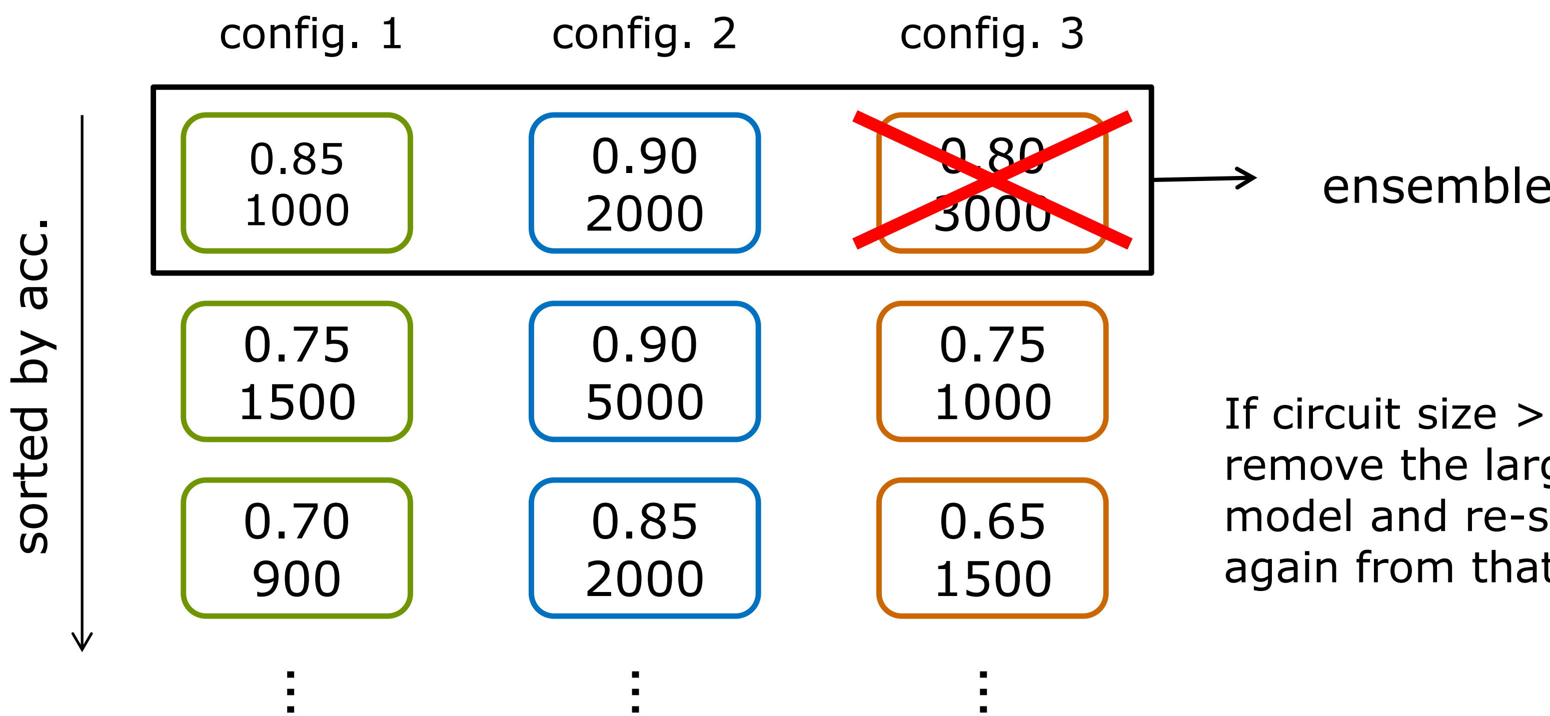


Under each configuration, train multiple models with different methods and hyper-parameters.

Bagging Ensemble

- Model selection heuristic





If circuit size > limit, remove the largest model and re-select again from that config.

EXPERIMENTAL RESULTS

Experimental Setup

- Our methods were implemented with ML packages scikit-learn [4] and Pytorch [5].
- The synthesized circuits were optimized by ABC [6].

[4] Pedregosa et al., 2011 [5] Paszke et al., 2019. [6] Brayton et al., 2010.

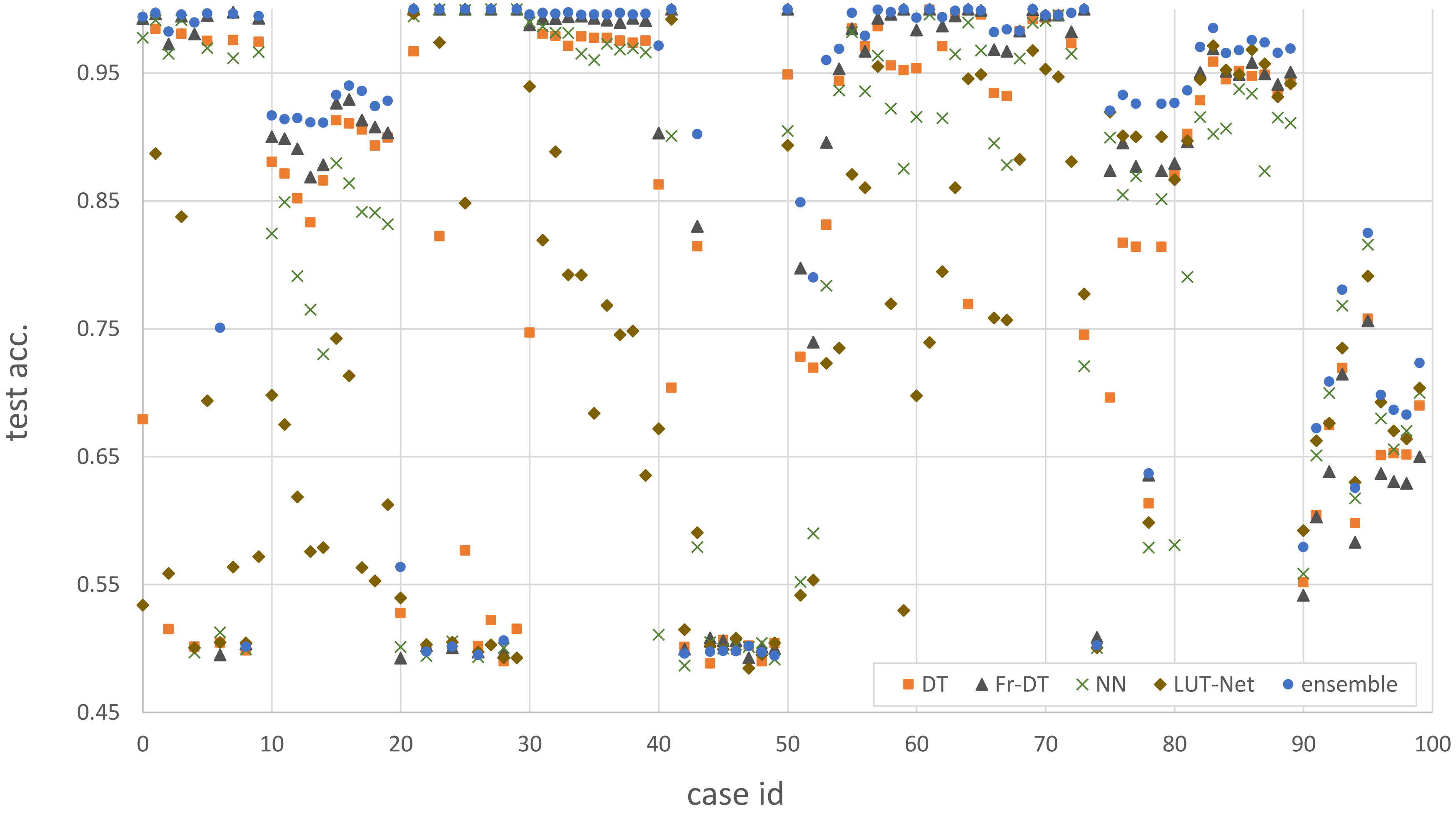
Experimental Results

method	avg. train acc.	avg. valid acc.	avg. test acc.	avg. size (#gate)
DT	90.41%	80.33%	80.15%	303.90
Fr-DT	92.47%	85.37%	85.23%	241.47
NN	82.64%	80.91%	80.90%	10981.38
LUT-Net*[7]	98.37%	72.78%	72.68%	64004.39
ensemble	-	-	87.25%	1550.33

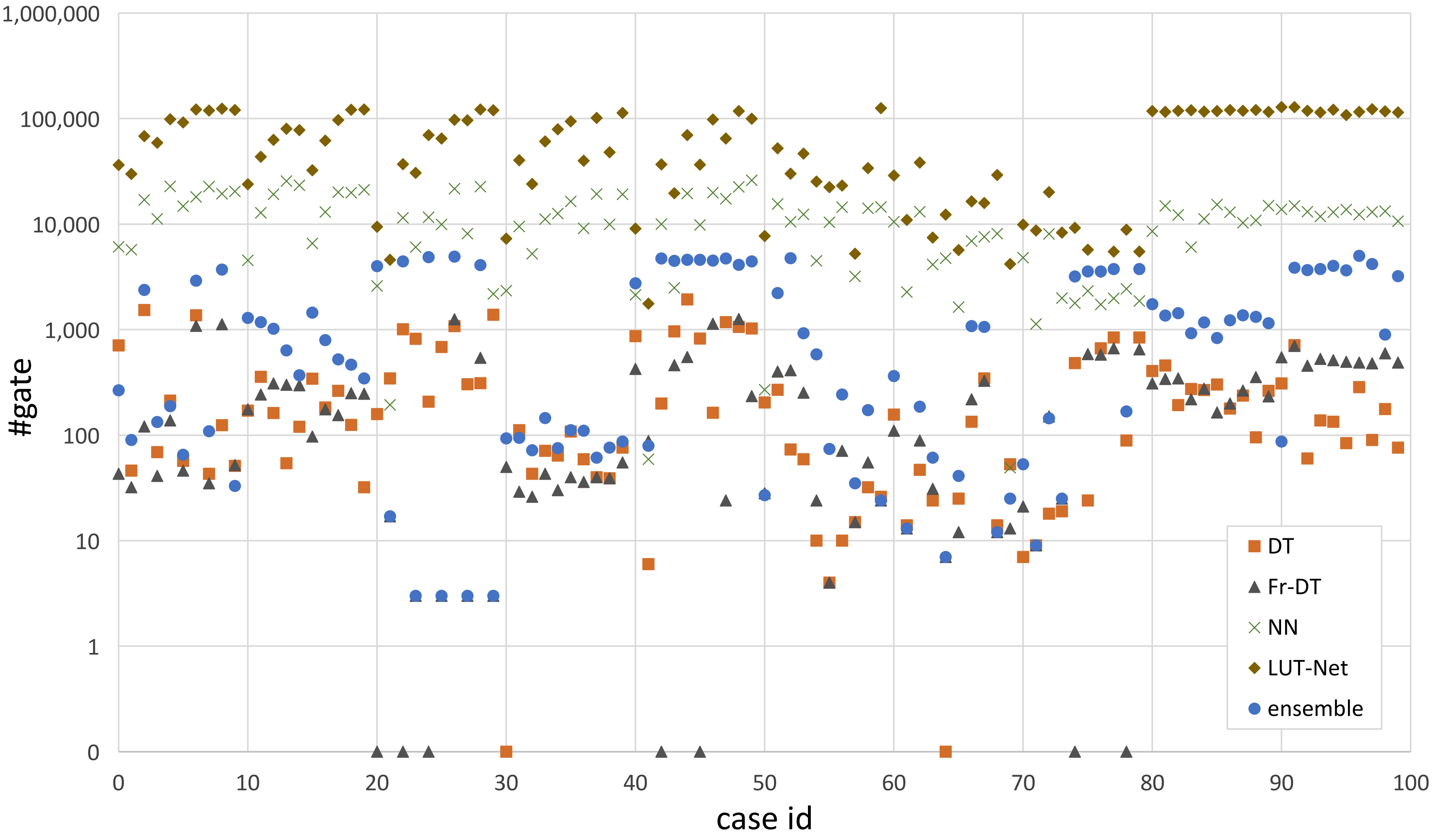
* LUT-Net is trained with the same avg. #connection as NN

[7] Chatterjee et al., 2018.

Accuracy Comparison



Circuit Size Comparison

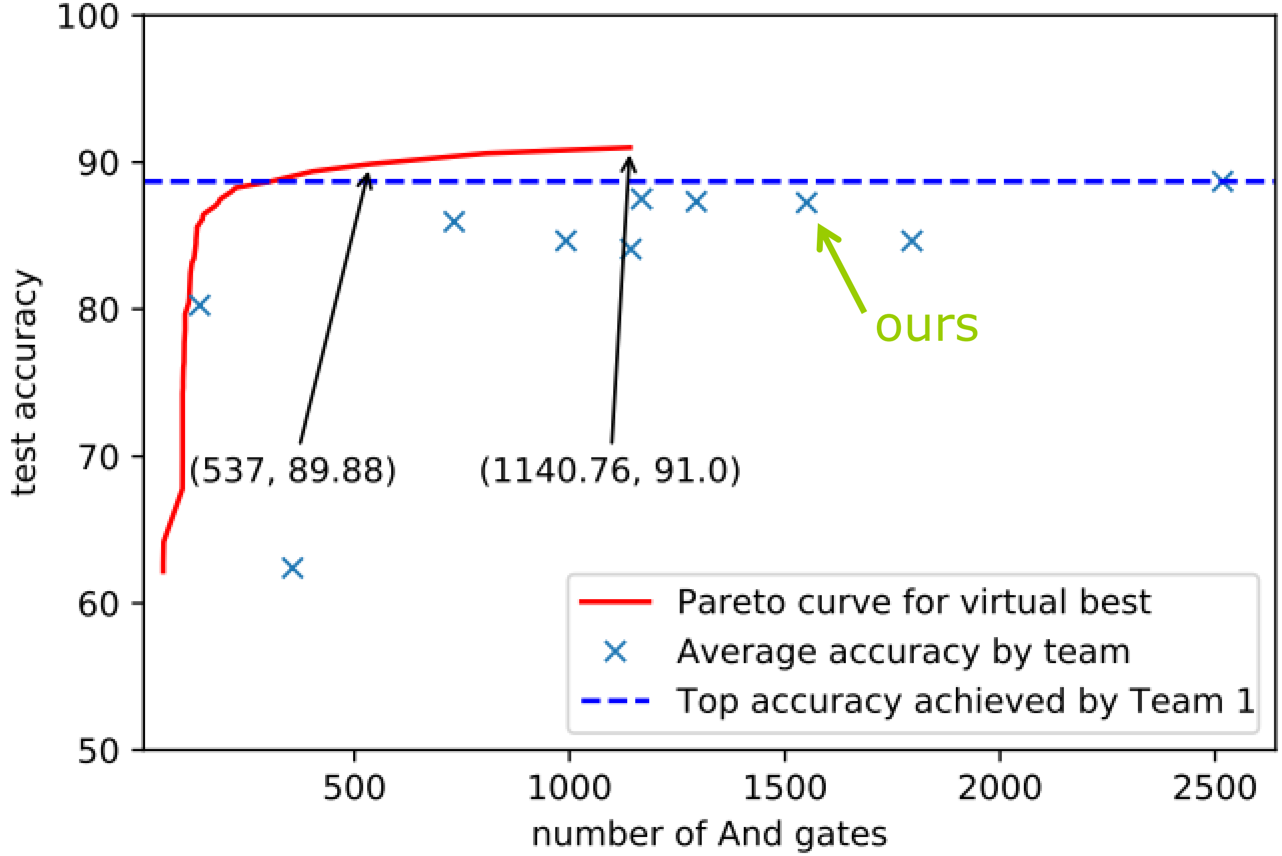


Contest Results

	team	↓ test accuracy	And gates	levels	overfit
	1	**88.69**	2517.66	39.96	1.86
	7	87.50	1167.50	32.02	**0.05**
	8	87.32	1293.92	21.49	0.14
ours →	3	87.25	1550.33	21.08	5.76
	2	85.95	731.92	80.63	8.70
	9	84.65	991.89	103.42	1.75
	4	84.64	1795.31	21.00	0.48
	5	84.08	1142.83	145.87	4.17
	10	80.25	**140.25**	10.90	3.86
	6	62.40	356.26	**8.73**	0.88

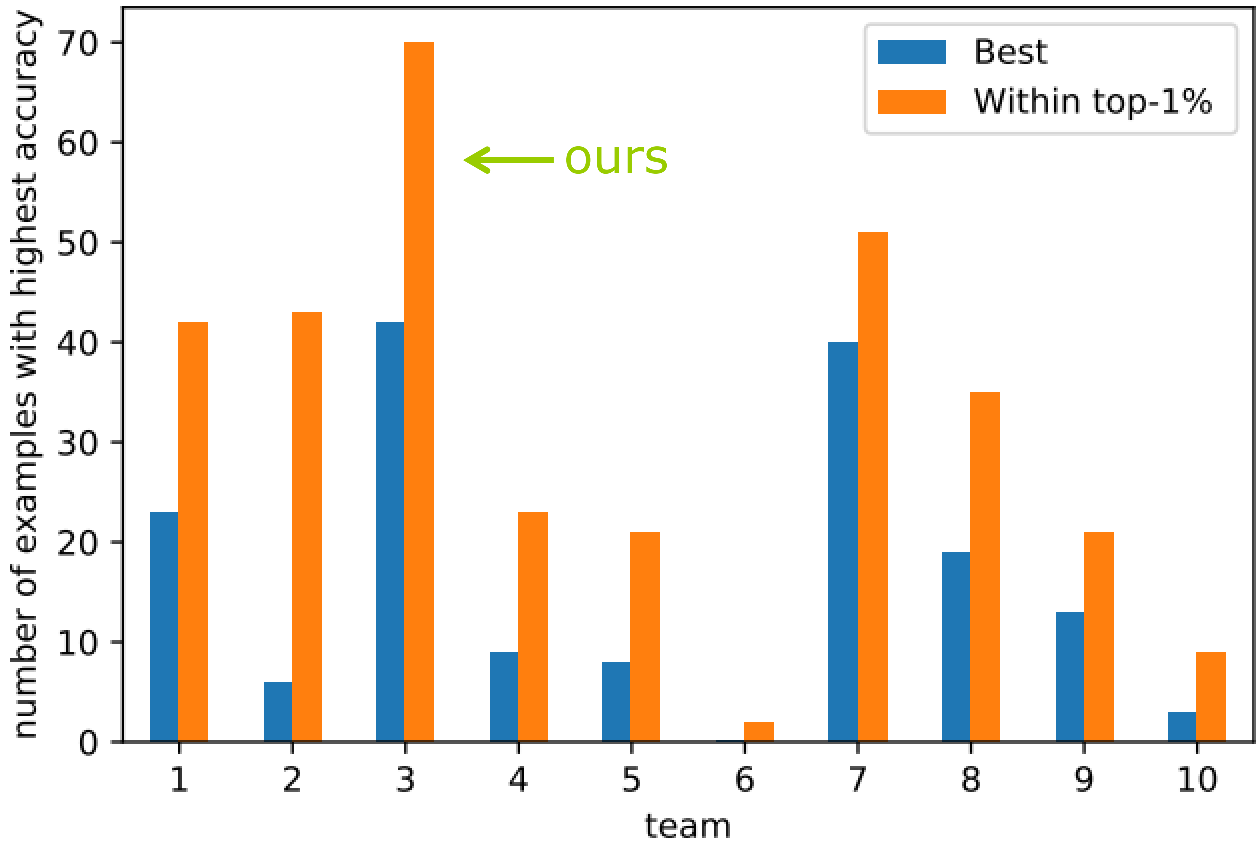
test acc. and circuit size summary of each team

Contest Results



#gate vs. test acc.

Contest Results



Top-accuracy results achieved by each team.

CONCLUSIONS

Conclusions

- Boolean functions can be learned by DT-based and NN-based methods.
- In our experiments, applying decision tree with fringe feature extraction could generally result in better model in terms of both accuracy and circuit size.
- NN models, though exceeded circuit size limit in many cases, they performed better in some other cases than DT models.
- After ensemble, we could achieve 87.25% accuracy on hidden test set.
- Our team achieved the **highest testing accuracy in most (42 out of 100) cases**, and ranked 4th in terms of the average testing accuracy.

THE END