Improving Deep Forest by Exploiting High-order Interactions

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* : equal contribution
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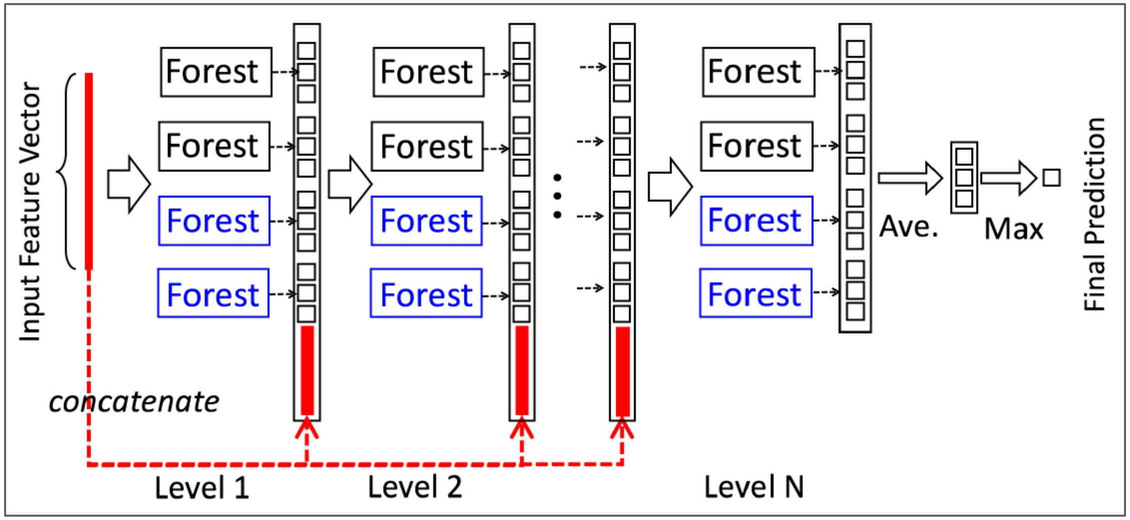
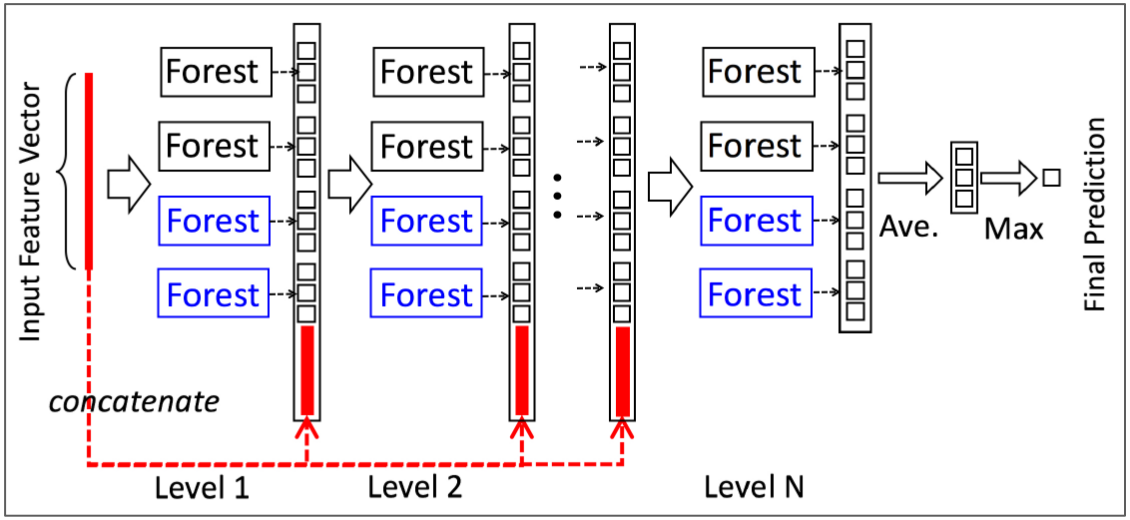
Deep Forest

- Realize deep learning with non-differentiable modules
- Excellent performance on categorical & mixed modeling tasks



Future **Issues** of Deep Forest :

- Representation learning ability and diversity are limited.
- High memory and time consumption.



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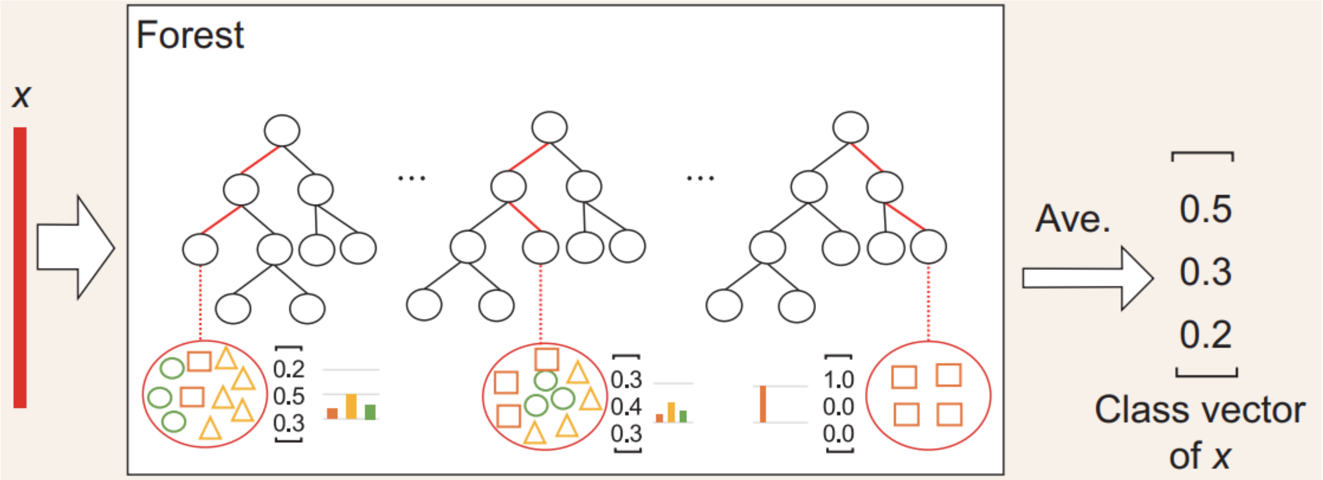

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No!

1. Lack of statistical importance.
2. Complex decision rules do not generalize well.

Random Intersection Trees

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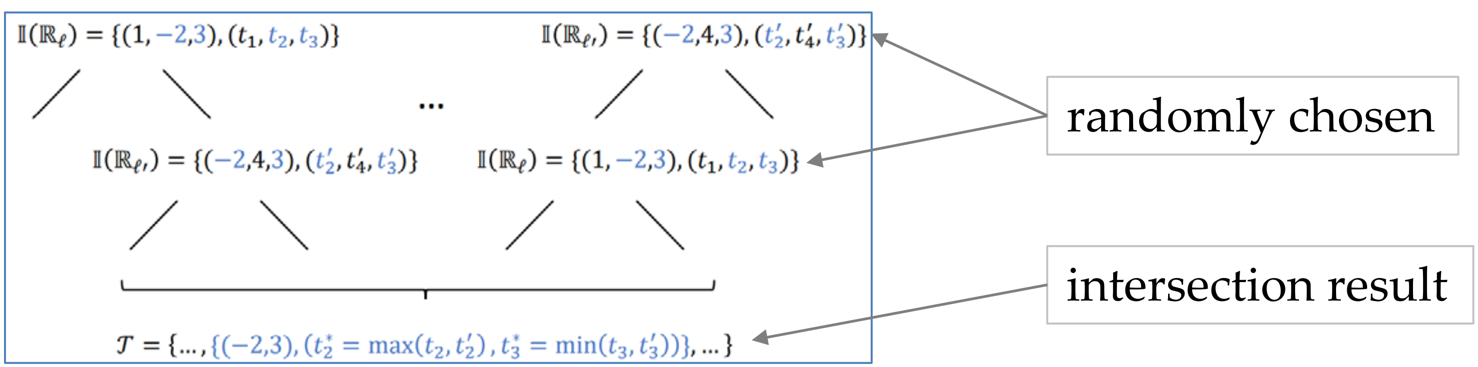
Perform **intersection** among random chosen feature interactions.

(intersection of decision rules == union of corresponding regions)



Utilizing discovered feature interactions

--- Activated Linear Combination (ALC)

$$\boldsymbol{r} = \{\ldots, \mathrm{ReLU}\big(-w_2(x_2 - t_2^*) + w_3(x_3 - t_3^*)\big), \ldots\}$$

Learning And Mining from DatA

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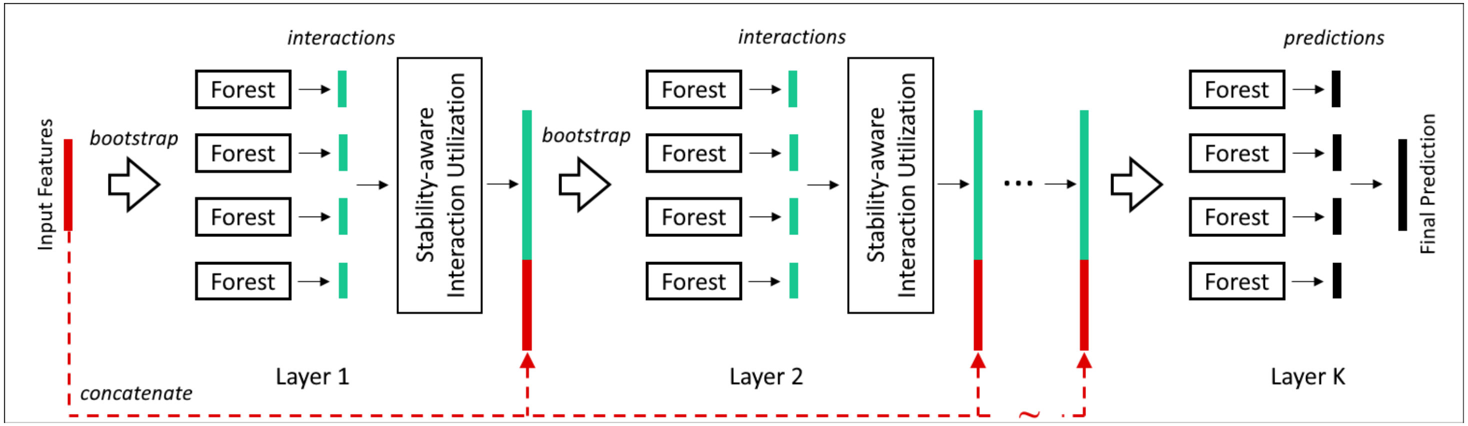
$\Downarrow$

Distributed Representation

--- core idea of deep learning methods.

Adaptive layer growth

--- retains high-order interactions.



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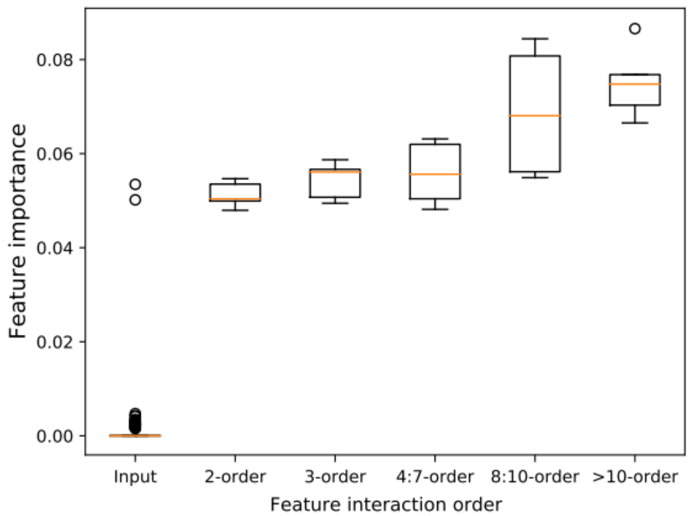

The importance of features with varying interaction orders

Experiments : UCI data

Datasets	hiDF	gcForest	$\text{gcForest}_{\text{CS}}$	Random Forests	XGBoost	GBDT	SVM
CoverType	**97.62 ± 0.08**	96.23 ± 0.10	96.09 ± 0.07	95.63 ± 0.07	94.48 ± 0.05	96.94 ± 0.11 •	71.47 ± 0.12
Adult	**86.90 ± 0.05**	86.17 ± 0.06	86.17 ± 0.09	85.15 ± 0.08	86.40 ± 0.00 •	86.12 ± 0.10	79.86 ± 0.00
Bank	**89.96 ± 0.21**	89.89 ± 0.26	89.95 ± 0.25 •	89.33 ± 0.17	89.13 ± 0.33	88.60 ± 0.25	89.75 ± 0.21
Credit Card	**82.00 ± 0.23**	81.74 ± 0.38 •	81.73 ± 0.20	81.71 ± 0.33	80.61 ± 0.36	81.24 ± 0.27	77.88 ± 0.01
Arrhythmia	**78.24 ± 1.62**	76.26 ± 1.49 •	74.51 ± 1.62	74.51 ± 2.13	75.16 ± 1.32	74.29 ± 3.15	60.66 ± 1.62
YearPredictionMSD	**75.89 ± 0.46**	75.49 ± 0.40	75.61 ± 0.30	73.41 ± 0.30	74.69 ± 0.21	75.85 ± 0.20 •	68.62 ± 0.62
Diabetes	**62.43 ± 0.23**	62.26 ± 0.36	62.37 ± 0.33 •	62.11 ± 0.24	61.00 ± 0.17	61.04 ± 0.45	54.99 ± 0.02
Satimage	**91.75 ± 0.06**	91.63 ± 0.12 •	91.58 ± 0.11	91.21 ± 0.05	90.65 ± 0.00	90.44 ± 0.09	88.60 ± 0.00
Crowdsourced Mapping	**65.07 ± 0.88**	64.93 ± 0.95	65.03 ± 0.56 •	63.47 ± 0.72	62.00 ± 0.00	62.53 ± 0.50	55.67 ± 0.00
Congestive Heart Failure	**90.16 ± 0.53**	88.61 ± 0.59	88.58 ± 0.27	87.90 ± 0.01	89.34 ± 0.01 •	88.83 ± 0.01	85.09 ± 0.00
win/tie/lose	—	10/0/0	10/0/0	10/0/0	10/0/0	10/0/0	10/0/0

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Computational complexity

Datasets	Method	Training time	Test time	Memory
Adult	hiDF	3208.7	13.1	2793.2
	gcForest	2763.8	541.3	29243.9
	$gcForest_{CS}$	1063.1	290.2	23272.7
Covertype	hiDF	4505.9	90.9	5562.5
	gcForest	2861.3	1519.4	61981.2
	$gcForest_{CS}$	1582.3	730.1	57658.8

Summary :

Interaction-based representation. & Multi-layer structure.

--- realize hierarchical distributed representation.

--- enhance representation diversity.

--- reduce computational complexity.

Thanks!