Splitting Stump Forests: Tree Ensemble Compression for Edge Devices

Fouad Alkhoury and Pascal Welke

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technische universität dortmund

Fraunhofer IAIS

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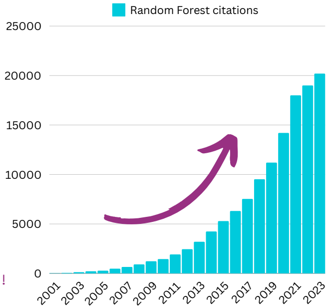
Breiman, Leo. ”Random forests.” Machine learning 45 (2001): 5-32.

138,466

citations

4th

most cited machine
learning paper ever!!



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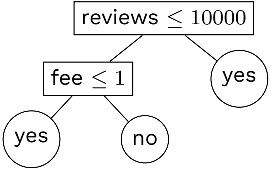

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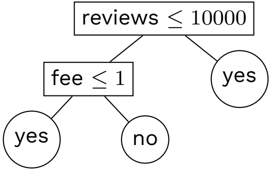

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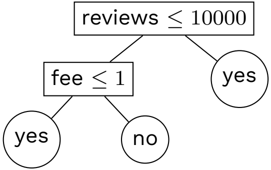

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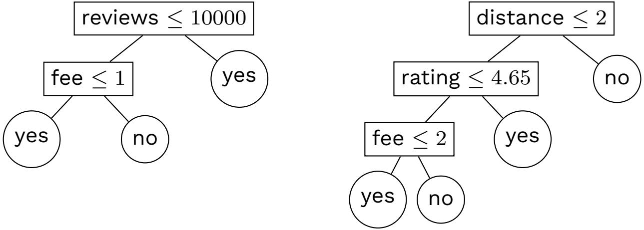

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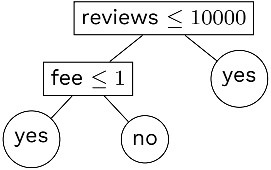

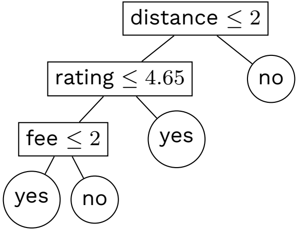

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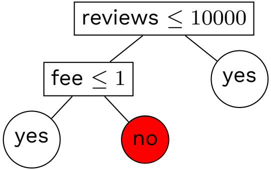

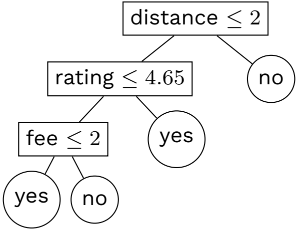

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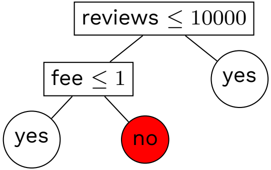

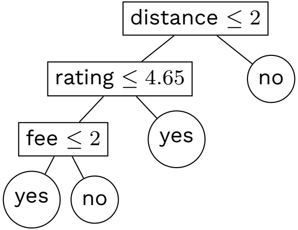

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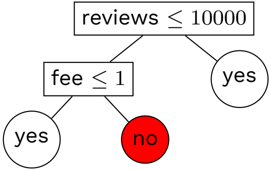

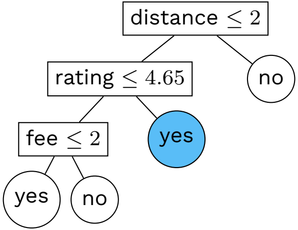

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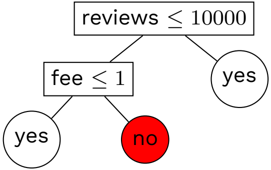

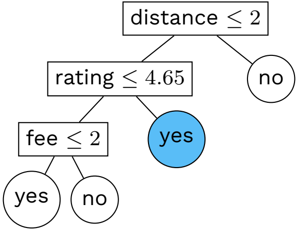

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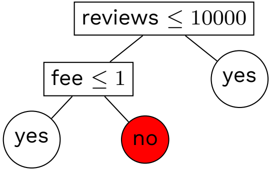

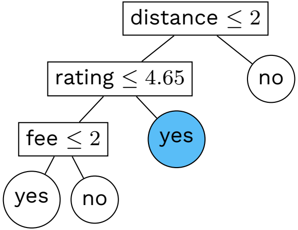

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❌ High variance and sensitivity

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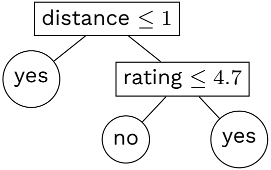

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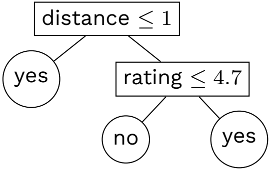

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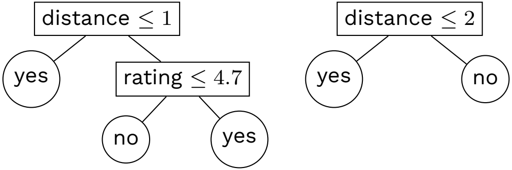

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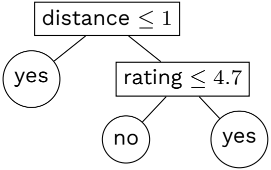

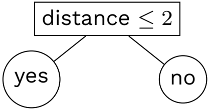

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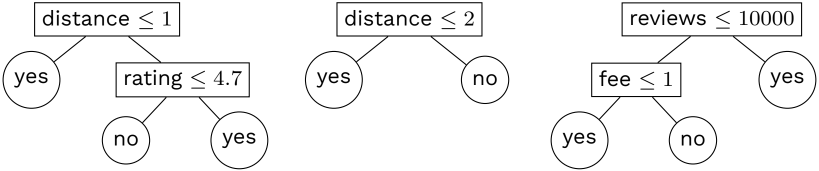

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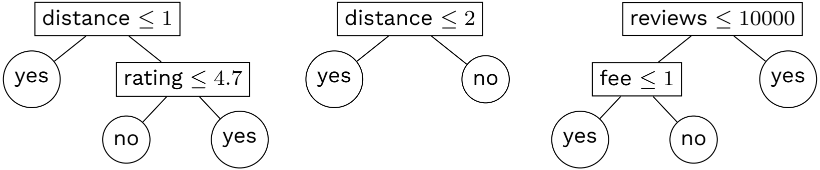

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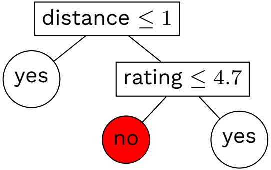

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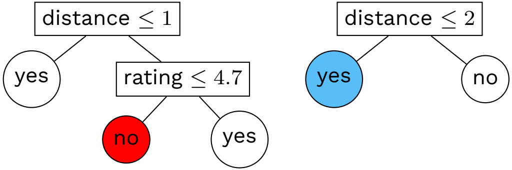

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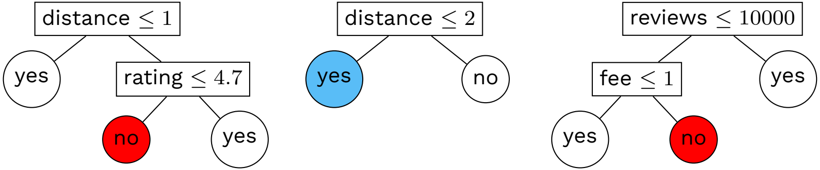

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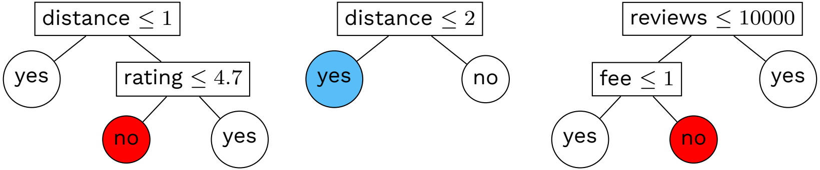

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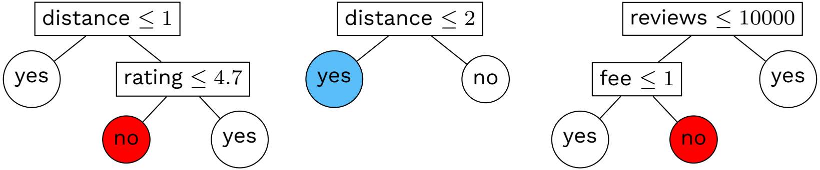

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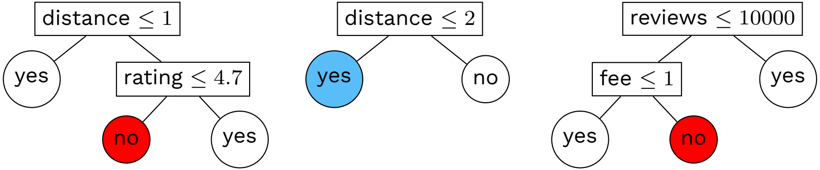

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❌ Larger model size

- Real-world datasets are very large (thousands/millions of examples.)

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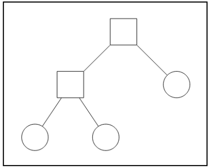

Small random forest

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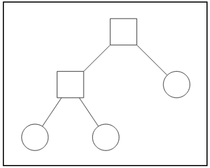

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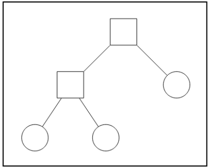

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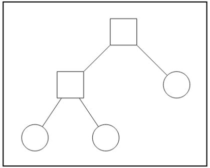

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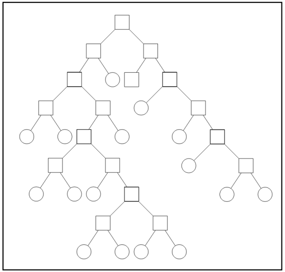

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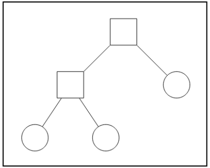

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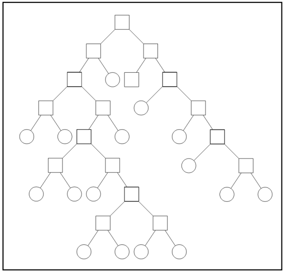
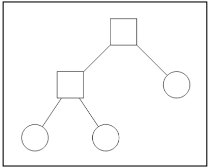


Large random forest

✅ higher predictive performance

- Real-world datasets are very large (thousands/millions of examples.)
- Some embedded devices have limited memory.

Microcontroller	Flash memory
ATmega169P	16 KB
Arduino Uno	32 KB
Arduino Mega	256 KB



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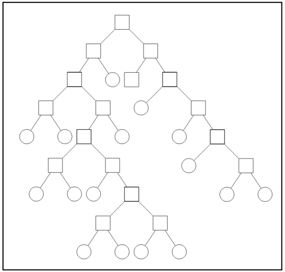

Large random forest

✅ higher predictive performance

❌ exceeds memory (~ 10 MB)

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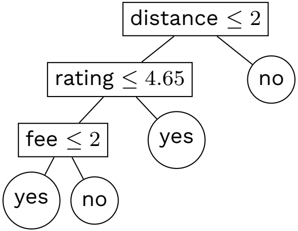
place	distance	fee	reviews	rating	visit
Pisa Tower	1.3	20	160800	4.7	yes
Cattedrale di Pisa	1.3	8	10923	4.8	yes
Palazzo blu	1.2	5	5205	4.6	no
Tuttomondo	1.8	0	2422	4.6	yes
Botanical Garden	1.0	4	3752	4.4	no
Piazza dei Cavalieri	0.8	0	10534	4.5	yes
Parco Migliarino	5.9	0	10602	4.5	no



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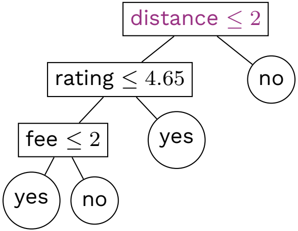

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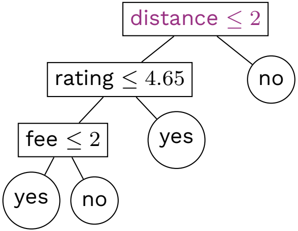

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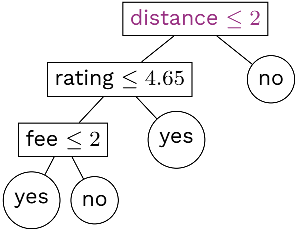

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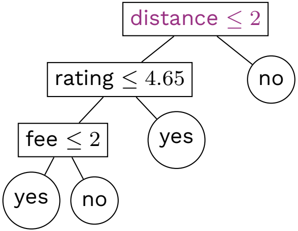

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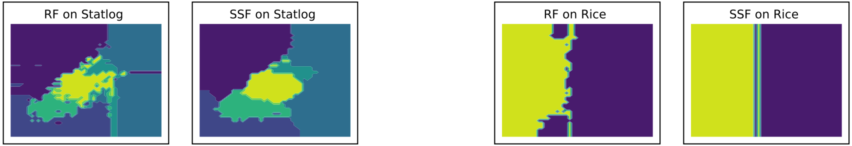
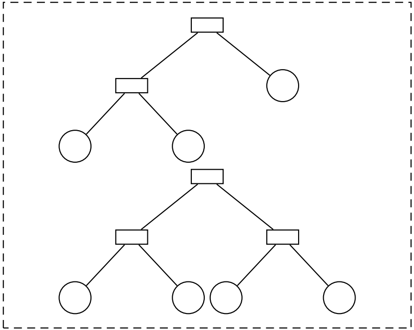


Splitting Stump Forests

1- Random Forest Training



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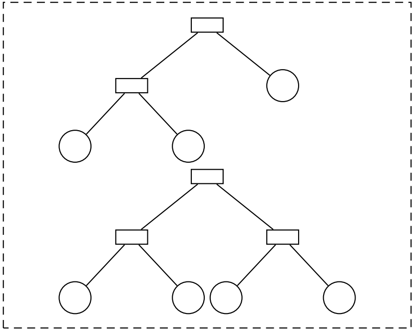
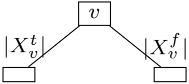


$$\boxed{score(v) \leftarrow \frac{min(|X_v^t|,|X_v^f|)}{|X_v^t|+|X_v^f|}}$$



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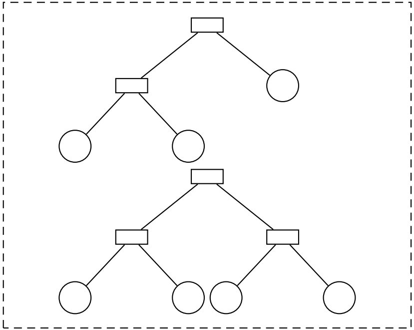
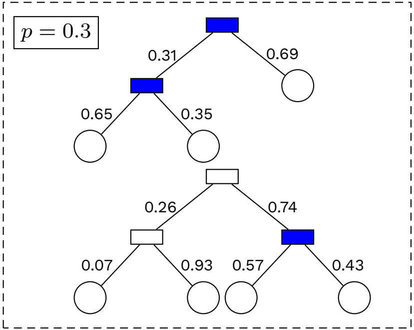


2- Splitting Node Selection



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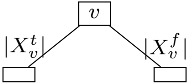

Balanced splits are selected.

3- Splitting Stump Transformation

$\boxed{\text{rating} \leq 4.7}$ $\boxed{\text{fee} \leq 1}$ $\boxed{\text{reviews} \leq 10000}$

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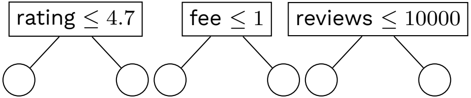

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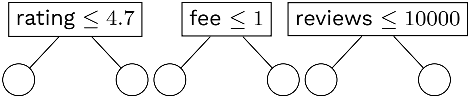

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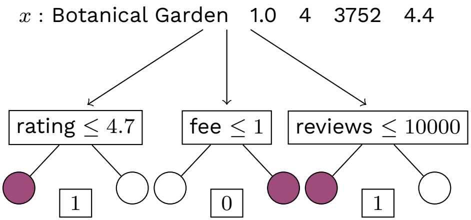

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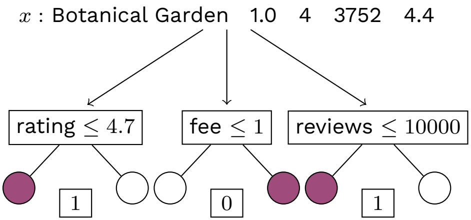

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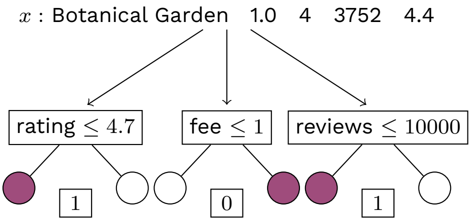
4- Training of SSF



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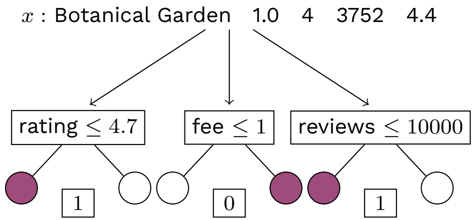

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$$\boxed{(f_{F'}(x), y) = (\{1,0,1\}, 0)}$$

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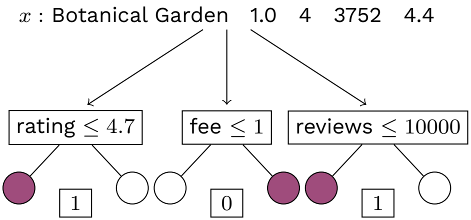

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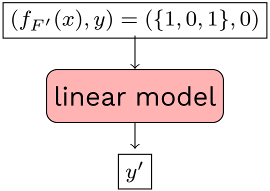

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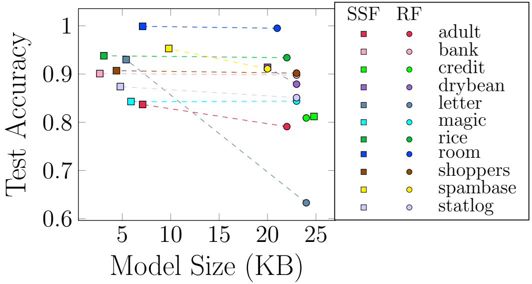
- Apply logistic regression to model the relationship between data representations and target variable

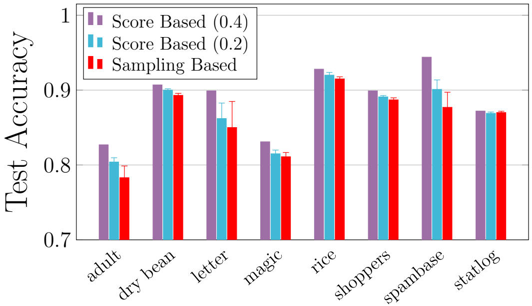
Experiments

- Splitting Stump Forests outperform Random Forest on small embedded devices.



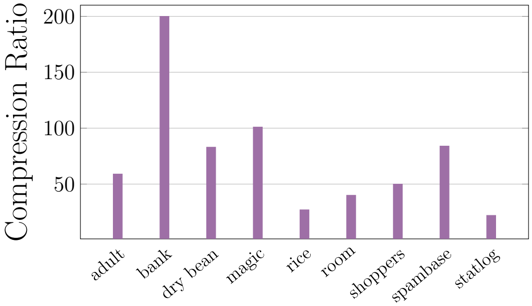
Experiments

- The selected splitting nodes are informative and not accidental.



Experiments

- The compression rate achieved while permitting a 2% accuracy drop.



Experiments

- Splitting Stump Forests outperform competitive methods.

Method		$d=5$	$d=10$	$d=15$	Global
RF	Acc.	5	4.69	3.23	4.31
(Random Forest)	Size	7	7	7	7
	Inf.	6.08	5.46	5.46	5.67
CCP	Acc.	6.46	6.62	6.85	6.64
(Cost Complexity Pruning)	Size	4	2.38	1.85	2.74
	Inf.	4.69	3.54	3.46	3.90
DREP	Acc.	4.23	3.62	3.69	3.85
(Diversity Regulaized Ensemble Pruning, 2012)	Size	3.62	4.69	5	4.44
	Inf.	3.07	3.08	2.85	3
IE	Acc.	4	3.23	3.38	3.54
(Individual Error, 2017)	Size	3.69	4.54	5.08	4.43
	Inf.	2.92	3.23	2.92	3.03
LR	Acc.	2.69	3.15	4.38	3.41
(Leaf Refinement, 2015)	Size	5.23	4.77	4.85	4.95
	Inf.	4.92	6.77	6.69	6.13
LR+L1	Acc.	2.23	2.77	2.69	2.56
(Joint Leaf Refinement, 2023)	Size	3.38	3.46	3	3.28
	Inf.	6	4.85	5.15	5.33
SSF	Acc.	**2**	**2.38**	**2.39**	**2.26**
	Size	**1.23**	**1.15**	**1.30**	**1.23**
	Inf.	**1.69**	**1.69**	**1.92**	**1.77**

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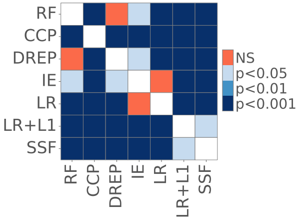

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- Large Random Forest is compressed into a compact model without sacrificing accuracy.
- The compressed models are suited for resource-constrained edge devices.

LAMARR

INSTITUTE FOR MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE

”Like the leaning Tower of Pisa, the Splitting Stump Forests find strength in balance”

Contact: alkhoury@iai.uni-bonn.de

Partner institutions:

technische universität dortmund

Fraunhofer IAIS

UNIVERSITÄT BONN

Fraunhofer IML

Institutionally funded by:

Bundesministerium für Bildung und Forschung

Ministerium für Kultur und Wissenschaft des Landes Nordrhein-Westfalen

	16 KB							32 KB						
Dataset	RF	CCP	DREP	IE	LR	LRL1	SSF	RF	CCP	DREP	IE	LR	LRL1	SSF
adult	82	81.9	80.5	82.9	84.4	85.7	**86.1**	85.1	82.3	83.4	84.3	85.9	**86.2**	86.1
	±0.4	±0.3	±0.2	±0.6	±0.4	±0.3	±0.3	±0.3	±0.4	±0.4	±0.5	±0.3	±0.3	±0.3
aloi	96.7	96.2	96.9	96.9	96.1	97.0	**97.1**	96.8	96.2	96.9	97	96.1	**97.1**	**97.1**
	±0.4	±0.1	±0.1	±0.1	±0.1	±0.1	±0.1	±0.1	±0.1	±0.1	±0.1	±0.1	±0.1	±0.1
bank	89.9	88.9	89.8	89.7	90.0	**90.2**	90.1	90	88.9	89.8	89.7	90.1	**90.4**	90.1
	±0.1	±0.5	±0.1	±0.1	±0.3	±0.3	±0.2	±0.1	±0.3	±0.1	±0.1	±0.2	±0.2	±0.1
credit	81	80.7	80.8	81.1	**81.4**	81.1	81.1	80.9	80.7	81	81.3	**81.4**	80.9	81.2
	±0.2	±0.3	±0.1	±0.2	±0.3	±0.1	±0.2	±0.1	±0.2	±0.1	±0.1	±0.2	±0.1	±0.1
dry bean	88.1	85.4	89.1	88.7	89.2	**91.8**	91.4	87.9	87.4	89.3	89.9	89.4	**91.8**	91.4
	±0.7	±0.3	±0.1	±0.3	±0.3	±0.1	±0.4	±1.0	±0.4	±0.5	±0.6	±0.5	±0.3	±0.4
letter	62.5	64.3	62.6	62.1	62.9	76.3	**93.0**	63.3	61.2	65.9	65.8	78.2	71.4	**93.0**
	±2.2	±1.1	±0.9	±1.2	±0.9	±0.9	±1.7	±3.6	±1.4	±1.0	±1.7	±1.5	±1.4	±1.9
magic	84.9	83.2	83.7	84.2	84.9	85.8	**86.3**	86	83.5	83.8	83.9	86.1	**86.5**	86.3
	±0.5	±0.9	±0.5	±0.5	±0.01	±0.2	±0.7	±0.7	±0.7	±0.3	±0.5	±0.6	±0.2	±0.4
rice	92.5	93.7	93.1	0.93	93.2	93.5	**93.8**	93.4	93.7	93.6	93.5	93.2	93.5	**93.8**
	±0.6	±0.7	±0.3	±0.4	±0.7	±0.1	±0.1	±0.7	±0.5	±0.2	±0.3	±0.6	±0.1	±0.1
room	99.2	97.0	99.5	99.6	99.2	99.8	**99.9**	99.5	99.3	99.7	**99.9**	99.2	99.8	**99.9**
	±0.3	±0.4	±0.1	±0.2	±0.6	±0.2	±0.2	±0.1	±0.2	±0.1	±0.2	±0.3	±0.1	±0.1
shoppers	87.2	86.9	90.1	91.0	**91.6**	91.3	90.7	90.2	86.9	90.3	91.2	91.6	**91.3**	90.7
	±1.5	±0.6	±0.3	±0.2	±0.4	±0.3	±0.4	±1.2	±0.2	±0.4	±0.1	±0.4	±0.2	±0.2
spambase	90.8	91.3	90.9	92.4	91.6	92.7	**95.3**	91.1	91.7	92.9	92.4	94.3	93.2	**95.3**
	±0.6	±0.4	±0.2	±1.0	±0.5	±0.2	±0.4	±0.6	±0.6	±0.6	±1.2	±0.4	±0.2	±0.2
statlog	85.2	84.1	84.7	84.8	84.9	86.5	**87.4**	85.1	84.9	84.8	84.7	87.1	**87.9**	87.4
	±1.6	±1.0	±0.4	±0.4	±0.8	±0.2	±0.3	±0.8	±0.6	±0.7	±0.6	±0.5	±0.2	±0.1
waveform	96.9	95.1	96.9	96.9	96.9	97.0	**97.1**	96.6	95.1	97	97	96.9	**97.2**	97.1
	±0.2	±0.2	±0.1	±0.1	±0.3	±0.1	±0.1	±0.2	±0.1	±0.1	±0.1	±0.2	±0.1	±0.1
avg rank	4.79	5.86	4.79	4.17	3.94	2.09	**1.54**	4.72	6.32	4.45	4.28	3.51	2.1	**1.88**