LAMARR
INSTITUTE FOR MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE

Resource Aware Machine Learning@Lamarr

Sebastian Buschjäger

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technische universität dortmund
Fraunhofer IAIS
UNIVERSITÄT BONN
Fraunhofer IML

Resource consumption of computing hardware

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Apple's Product Environmental Report[https:/www.apple.com/environment/]

(excluding end-of-life processing here)

iPhone-14	1 Year [kg]	3 Years [kg]	10 Years [kg]
Production	48.19	48.19	48.19
Transport	1.22	1.22	1.22
Useage	3.66	10.98	36.6

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Clear Use an iPhone-14 for around 13 years to break even with production costs!

But Average life-cycle for an iPhone-14 are 3 to 4 years

A Closer Look at Older / Smaller Hardware

Common Microcontroller Units[Branco et al. 2019]

MCU	CPU	Flash	(S)RAM
Arduino Uno (ATMega128P)	16MHz	32KB	2KB
Arduino Mega (ATMega2560)	16MHz	256KB	8KB
STM32L0 (Cortex-M0)	32MHz	192KB	20KB
Arduino MKR1000 (Cortex-M0)	48MHz	256KB	32KB
STM32F2 (Cortex-M3)	120MHz	1MB	128KB
STM32F4 (Cortex-M4)	180MHz	2MB	384KB
RPi A+	700MHz	SD Card	256MB
RPi Zero	1GHz	SD Card	512MB
RPi 3B	4@1.2GHz	SD Card	1GB
Apple A7 (iPhone 5)	2@1.4 Ghz	16-64 GB	1GB

Empirical Risk Minimization Revisited

$$f^* = \arg\min_{f \in \mathcal{F}} \frac{1}{N} \sum_{(x,y) \in \mathcal{D}} \ell(f(x), y) + \lambda R(f)$$

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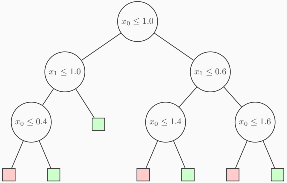
Use resource-friendly model class $\mathcal{F}$ directly
$\Rightarrow$ Guaranteed resource consumption, but maybe weak loss

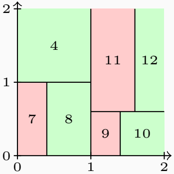
Guide selection via regularization
$\Rightarrow$ Direct trade-off between loss and model complexity via λ

Additive Tree Ensembles

In many applications Random Forests are outperforming Deep Learning methods

Axis-aligned Decision Trees Split data into groups of increasing label purity





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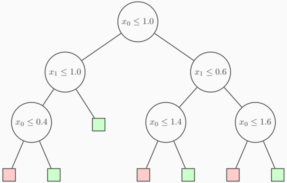

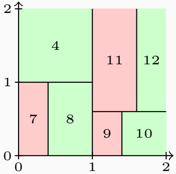

$$h(x) = \sum_{i=1}^{L} y_i \pi_i(x),\ \pi_i(x) = 1 \text{ if x in leaf i else 0}$$

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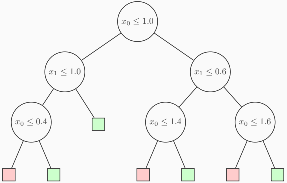

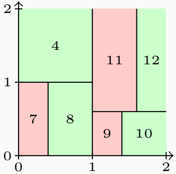

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Random Forest Train multiple DTs on bootstrap samples and average predictions

$$f(x) = \frac{1}{M} \sum_{i=1}^{M} h_i(x)$$

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Can we compute a small *and* accurate tree ensemble?

Ensemble Pruning Revisited

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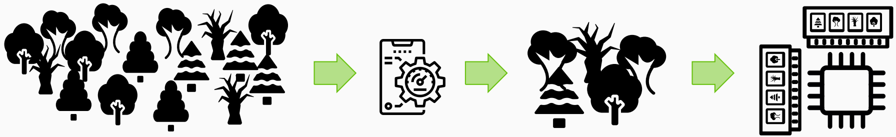

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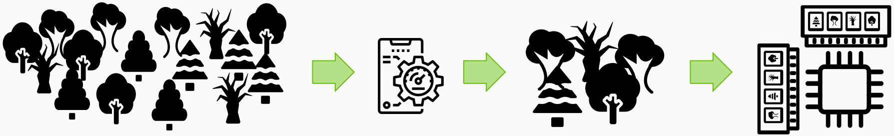

Formally

$$f_w(x) = \frac{1}{K}\sum_{i=1}^{M} w_i h_i(x)$$

solve

$$\arg\min_{w \in \{0,1\}^M} \sum_{(x,y)\in\mathcal{S}} \ell\left(f_w(x), y\right) \text{ s.t. } \|w\|_0 = K \ll M$$

Ensemble Pruning Revisited (2)

Ensemble Pruning Standard method to select fewer trees in a forest

- **Ranking**[Martínez-Muñoz and Suárez 2004, Li et al. 2012, Margineantu and Diettereich 1997]
  Assign a score to each tree and select the top-k trees
- **Clustering**[Giacinto et al. 2000, Bakker and Heskes 2003, Lazarevic and Obradovic 2001, ...]
  Cluster trees and then select a representative from each cluster
- **MQIP**[Cavalcanti et al. 2016, Zhang et al. 2006]
  Construct Mixed Quadratic Integer Program to select trees
- **Ordering**[Jiang et al. 2017, Lu et al. 2010, Margineantu and Dietterich 1997, ...]
  Order the trees according to their overall contribution and select the first K trees

Leaf-Refinement

Idea 2 Use a small forest from the beginning and refine it[Ren et al. 2015, Buschjäger and Morik 2021]

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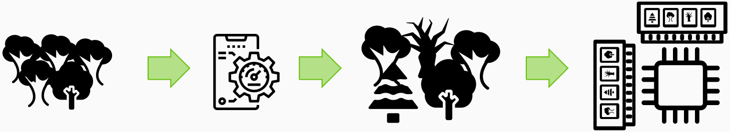

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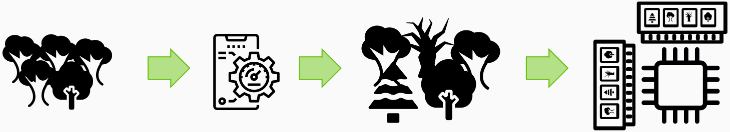

Formally Perform SGD on the leaf nodes $\theta_i = (y_{i,1}, \dots, y_{i,L_i}), \quad \theta = [\theta_1, \dots, \theta_M]$

$$\arg\min_{\theta \in \mathbb{R}^{M \cdot L_1 \dots L_M}} \sum_{(x,y) \in \mathcal{S}} \ell\left(f_\theta(x), y\right)$$

Leaf-Refinement and Pruning combined

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$$\underset{\substack{w \in [0,1]^M \\ \theta \in \mathbb{R}^{M \cdot L_1 \dots L_M}}}{\arg\min} \sum_{(x,y) \in \mathcal{S}} \ell\left(f_{w,\theta}(x), y\right) + \lambda \|w\|_1$$

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Relaxed Constraints

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Optimization over both parameters

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Regularization to enforce pruning

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Relaxed Constraints

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Regularization to enforce pruning

Challenge Constraint optimization $\rightarrow$ use Proximal Gradient Descent

Experiment 1: Compare with Vanilla Random Forest

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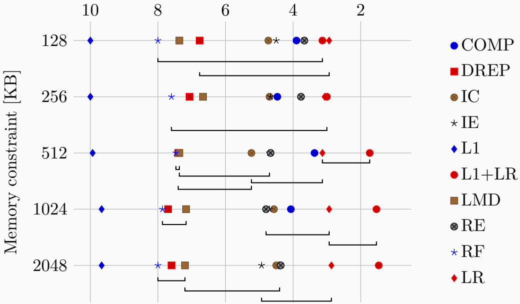
RF	accuracy [%]	86.78	98.58	90.39	93.42	88.98	96.53
	model size [MB]	24.99	32.85	24.99	14.95	24.99	56.99
LR+L1	accuracy [%]	87.25	99.78	90.5	95.55	92.49	98.05
	model size [MB]	0.06	3.52	0.07	5.88	14.37	28.49

Experiment 2: Perform systematic experiments on more datasets

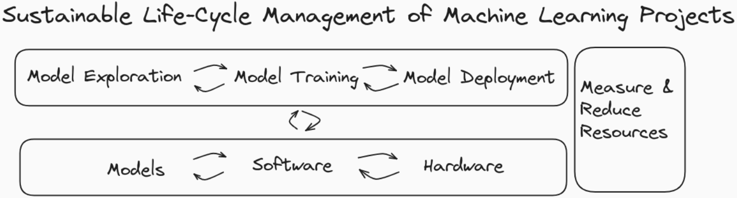
Comparison with more algorithms on more datasets

15 datasets, 10 methods, 920 hyperparameter configs per datasets

13 800 models cross-validated



Towards Sustainable Life Cycle Management of ML Projects



Possible Research Questions

- How can we measure the {energy, performance, embodied carbon} of ML systems?
- What {abstraction,language} is required to {reason about, optimize} ML systems?
- How can we reduce {bandwidth, voltage, model size, runtime}?
- Can we re-use old/existing hardware for new models?
- Is {anytime, online, preiodical} training more efficient than batch processing?
- How do you manage a fleet of ML systems?

Summary

Use the iPhone-14 for $\approx$ 10 years to make it worth building it

Ensmeble Pruning

- Ensemble Pruning removes unncessary trees; Leaf-Refinement improves trees
- Leaf-Refinement + Pruning leads to smaller *and* better models

Sustainable Life Cycle Management of ML Projects

- Explore ML Projects while looking at resource constraints
- Explore the entire pipeline of ML projects from training to deployment