Random Planted Forest
A Directly Interpretable Tree Ensemble

Meyer, J. T.[5] Burk, L.[1,2,3,4] Hiabu, M.[6] Mammen, E.[5]

[1]Leibniz Institute for Prevention Research and Epidemiology – BIPS
[2]LMU Munich [3]University of Bremen
[4]Munich Center for Machine Learning (MCML)
[5]Heidelberg University [6]University of Copenhagen

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Motivation

- Individual decision trees: Easy to interpret

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- Additive models (LM, GAM, ...) can provide both
- → Need to manually specify interactions in model fit

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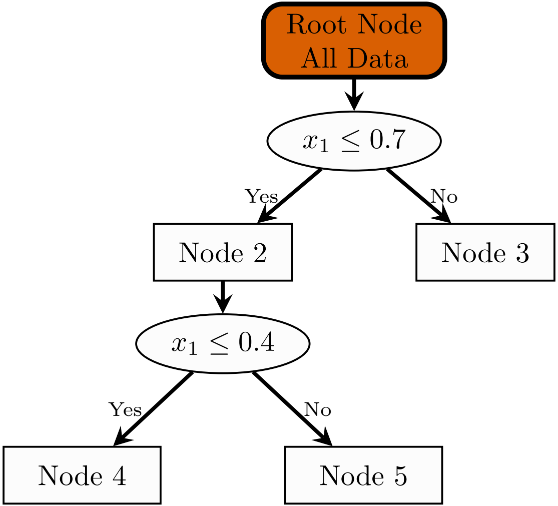
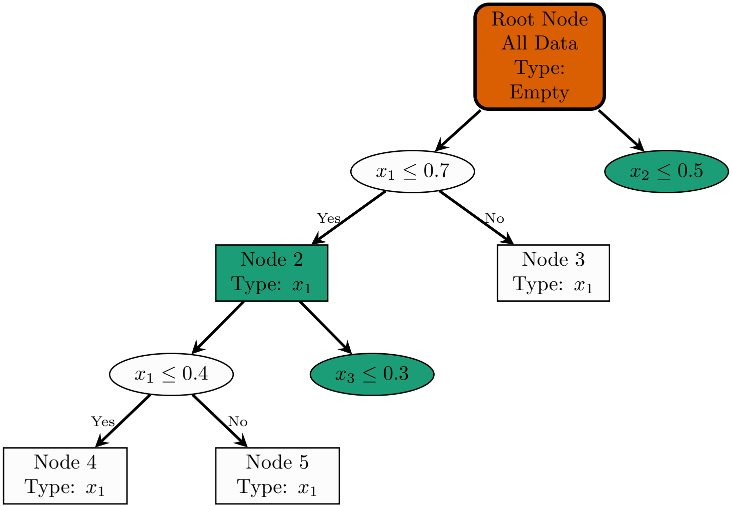
$$
\begin{aligned}
\hat{m}(\mathbf{x}) = \hat{m}_0 &\\
&+ \underbrace{\hat{m}_1(x_1) + \hat{m}_2(x_2) + \hat{m}_3(x_3)}_{\text{Main effects}}\\
&+ \underbrace{\hat{m}_{1,2}(x_1, x_2) + \hat{m}_{1,3}(x_1, x_3) + \hat{m}_{2,3}(x_2, x_3)}_{\text{2nd order interactions}}\\
&+ \underbrace{\hat{m}_{1,2,3}(x_1, x_2, x_3)}_{\text{3rd order interaction}}
\end{aligned}
$$

Trees in Random Forest



Planted Trees



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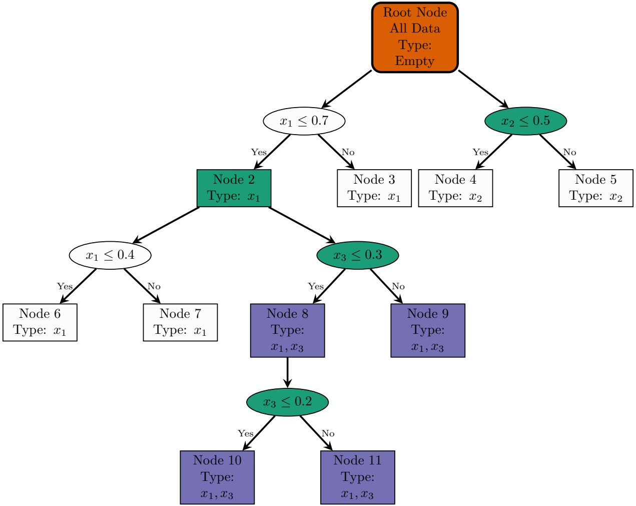

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- Prediction is average of additive $\hat{m}_S$ estimates

Application Example

- `Bikeshare` regression dataset [1]

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- Average prediction: $\hat{m}_0 \approx 143.7$

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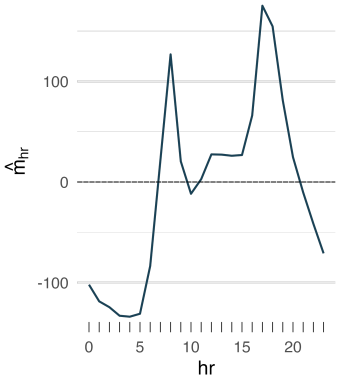
Main Effects



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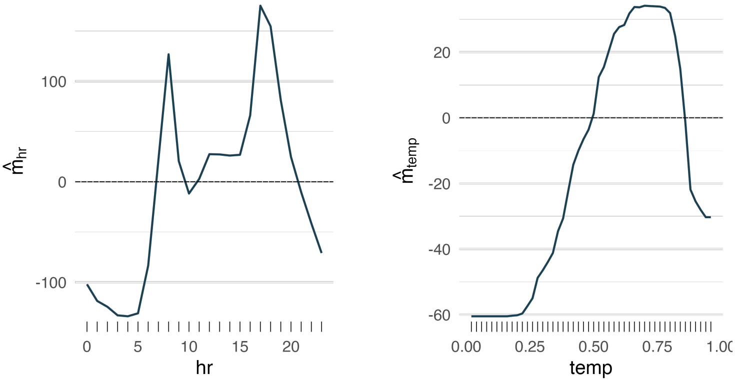

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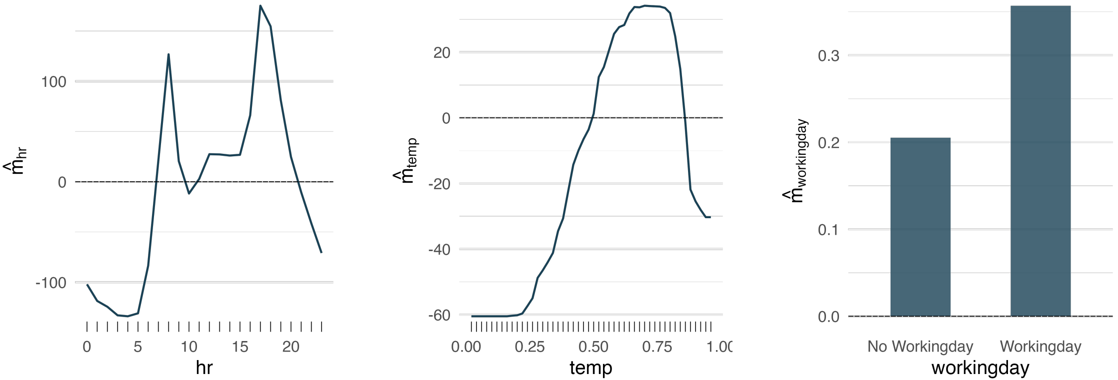
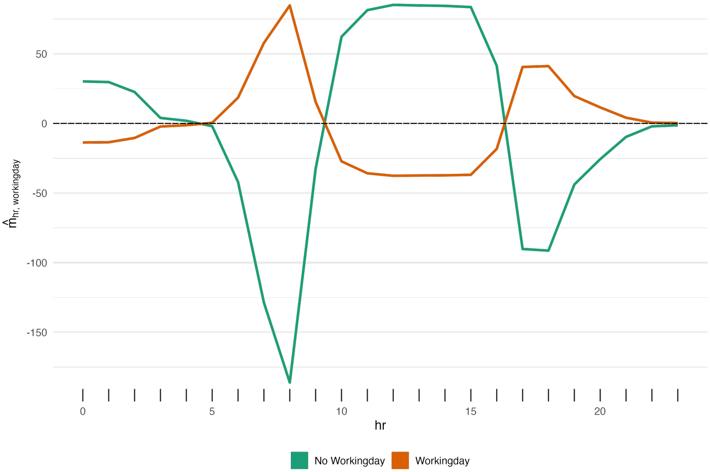


Hour × Working Day: "Rush Hour Effect"



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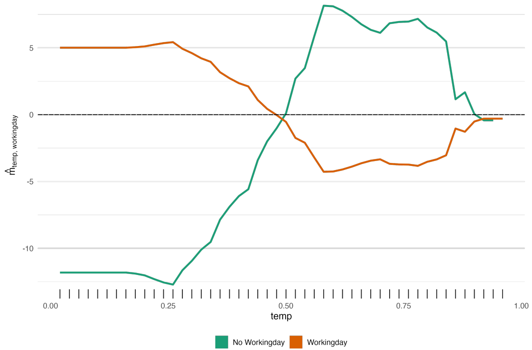
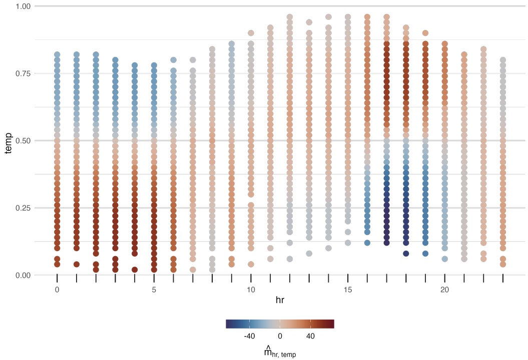
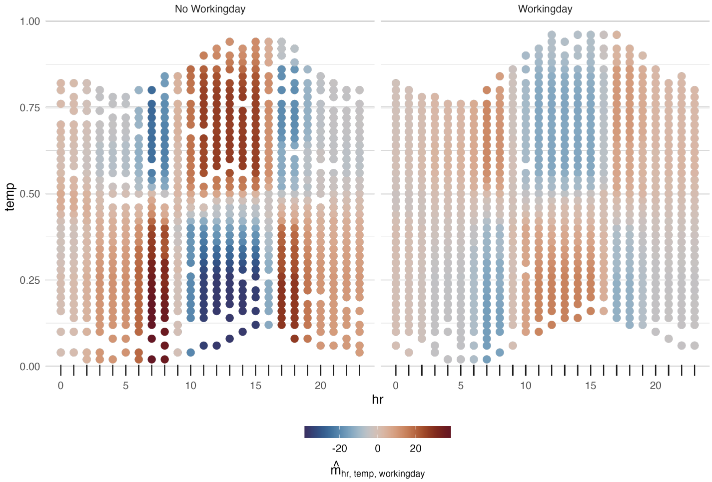




3rd Order Interaction



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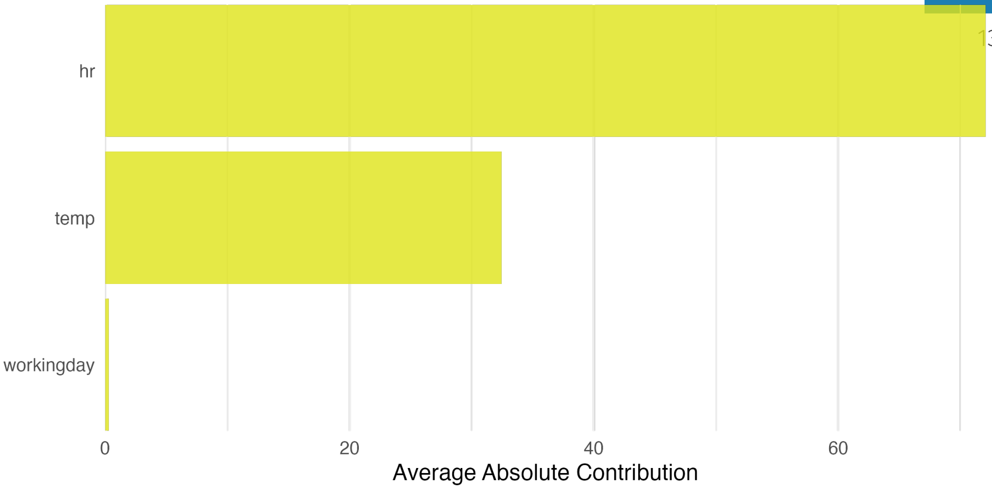
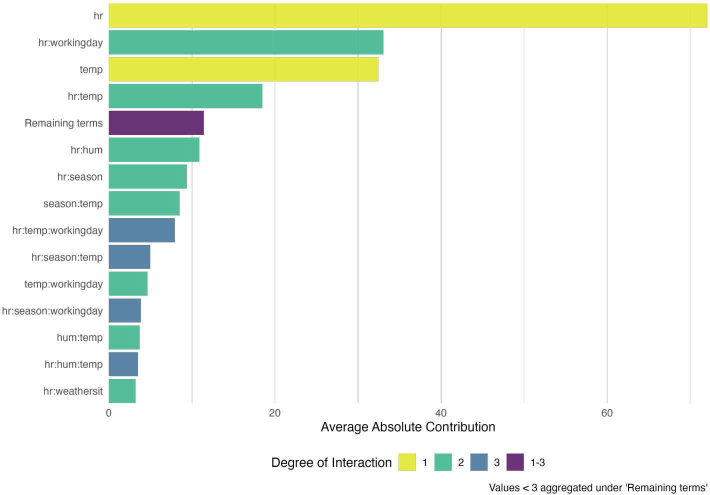
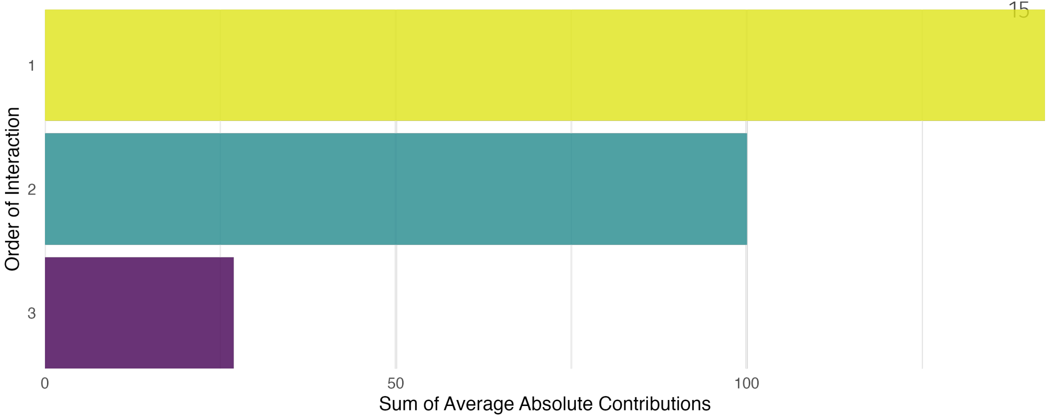
Feature Importance per Main Term



Feature Importance per All Terms



Feature Importance by Order of Interaction



Related work

Glex[2]: Same ANOVA decomposition but generally for tree-based methods (e.g. XGBoost)

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- **Benefit**: Use existing / well known / well optimzied algorithm
- **Drawback**: Computationally intensive post-hoc computation

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No Free Lunch

Better interpretibility → worse predictive performance?

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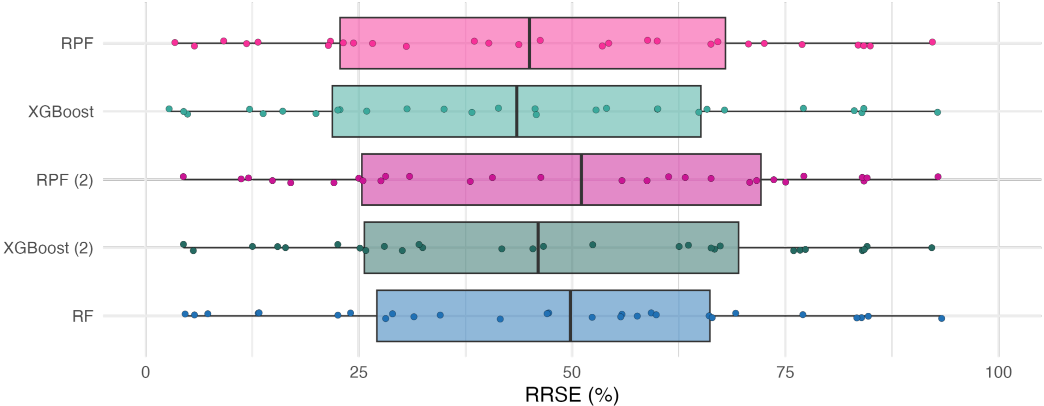
- 28 datasets from OpenML-CTR23 regression benchmark suite [3]
- Also comparing XGBoost / RPF with interactions restrained to 2
- Generally XGBoost best, RPF and RF closely behind

[3] Fischer et al. (2023)

Benchmark Results (Aggregated)

- Root-Relative Squared Error (RRSE) $\sqrt{\frac{SSE(Y,\hat{Y})}{SSE(Y,\bar{Y})}}$



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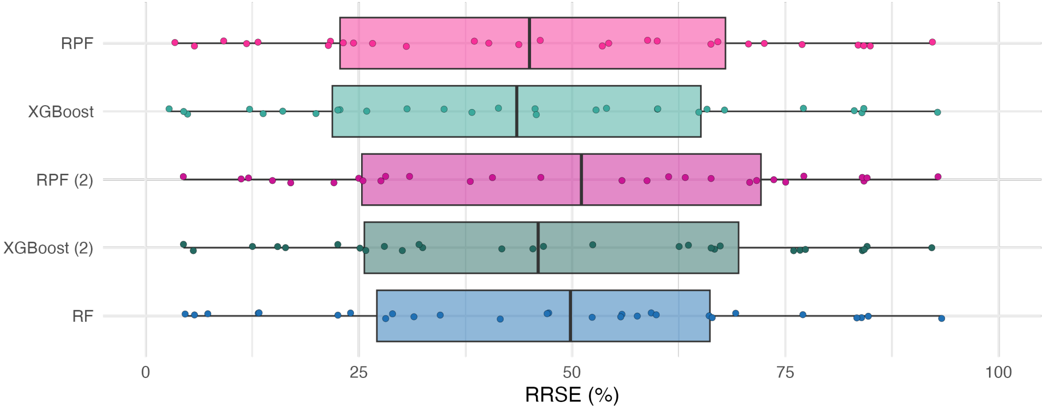
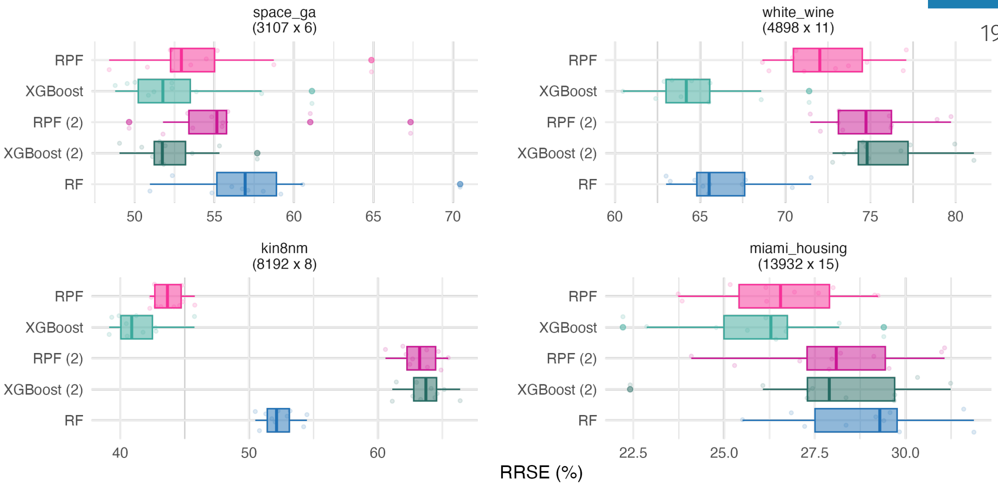
- Featureless model scores 1, perfect score 0



Results for Selected Tasks



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- (~) Predictive performance worse but similar to comparable algorithms
- (-) Computationally heavy for large data
- (+) R package available [4]

[4] github.com/PlantedML/randomPlantedForest

Thank you for your attention!

Slides:

www.leibniz-bips.de/en

Contact
Lukas Burk
Leibniz Institute for Prevention Research
and Epidemiology – BIPS
Achterstraße 30
D-28359 Bremen
burk@leibniz-bips.de

References I

Fischer, Sebastian Felix et al. (2023). "OpenML-CTR23 – A Curated Tabular Regression Benchmarking Suite". In: AutoML Conference 2023 (Workshop).

Hiabu, Munir, Joseph T. Meyer, and Marvin N. Wright (Apr. 11, 2023). "International Conference on Artificial Intelligence and Statistics". In: ISSN: 2640-3498 Citation Key: hiabu2023unifyinglocala. PMLR, pp. 7040–7060.