Random Planted Forest
A Directly Interpretable Tree Ensemble

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→ **Random Planted Forest** (RPF): Additive Random Forest

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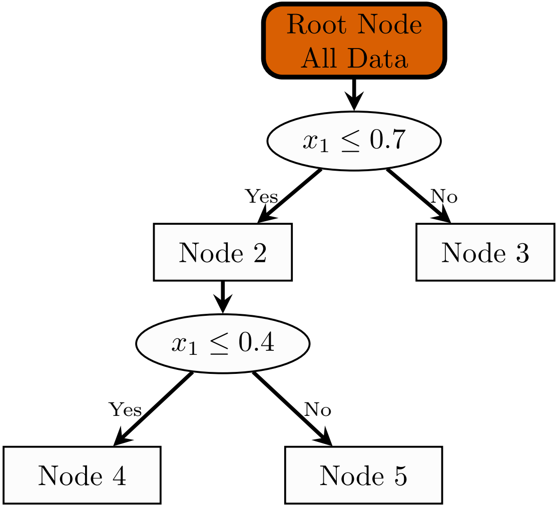
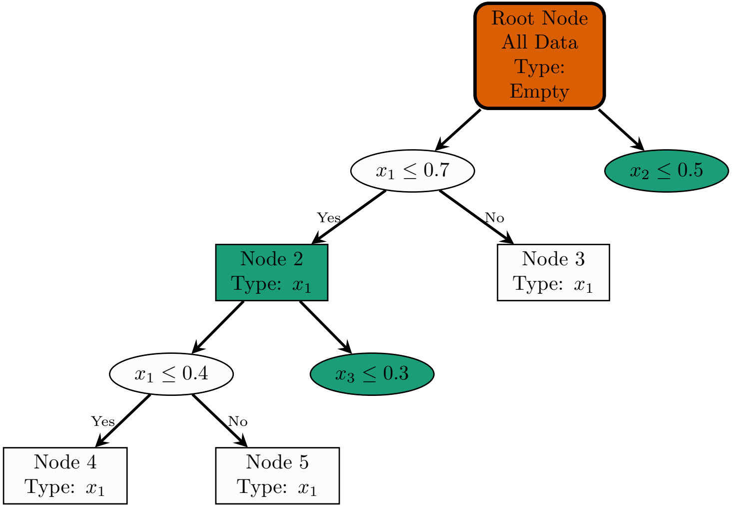
$$
\begin{aligned}
\hat{m}(\mathbf{x}_i) = & \hat{m}_0 + \\
& \underbrace{\hat{m}_1(x_1) + \hat{m}_2(x_2) + \hat{m}_3(x_3)}_{\text{Main effect terms}} + \\
& \underbrace{\hat{m}_{1,2}(x_1, x_2) + \hat{m}_{1,3}(x_1, x_3) + \hat{m}_{2,3}(x_2, x_3)}_{\text{2nd order interactions}} + \\
& \underbrace{\hat{m}_{1,2,3}(x_1,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

Trees in Random Forest



Planted Trees (I)



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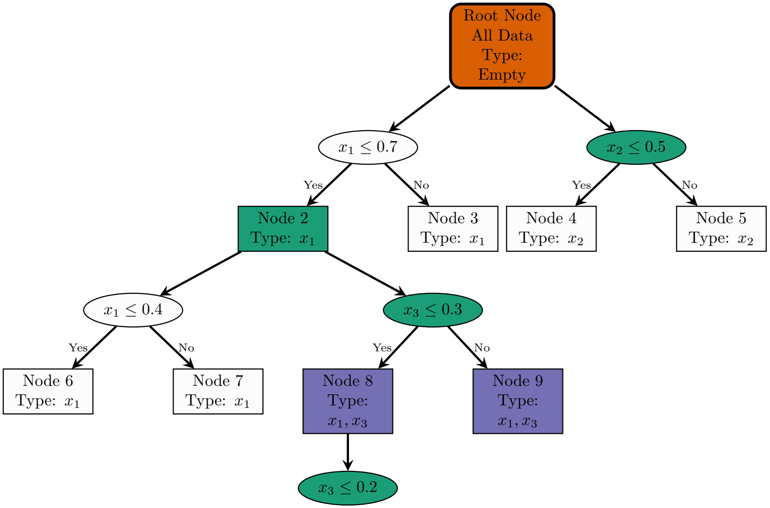

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- Degree of interaction can be constrained
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- Prediction built up incrementally, guided by residuals (cf. Gradient Boosting)

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- Average prediction: $\hat{m}_0 \approx 144$

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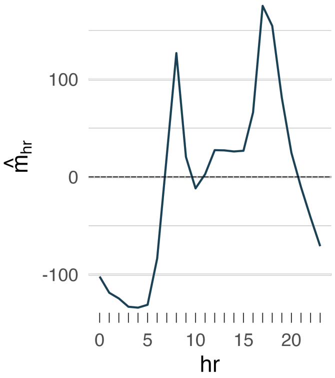
Main Effects



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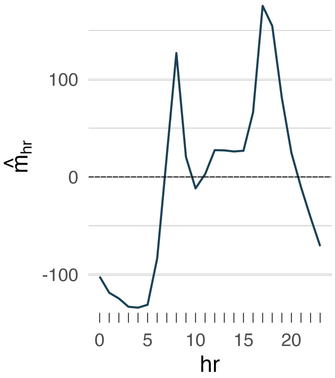

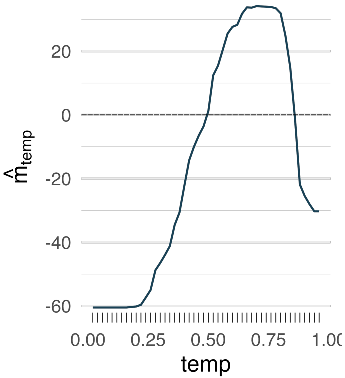

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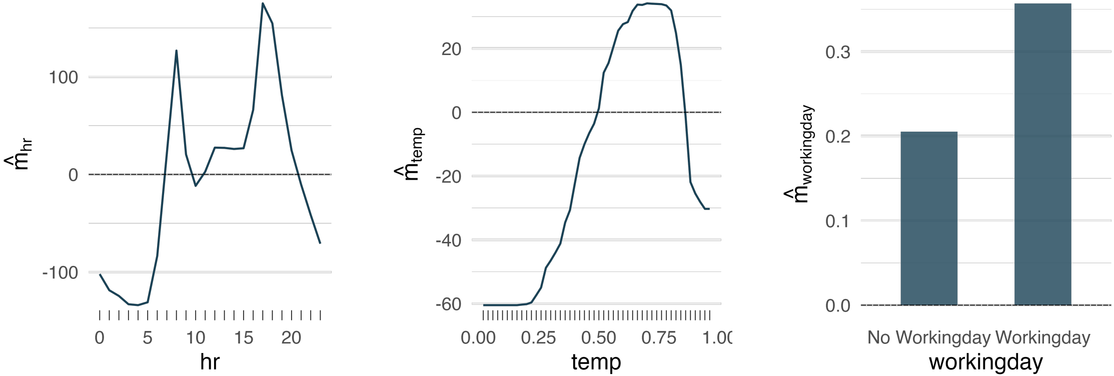

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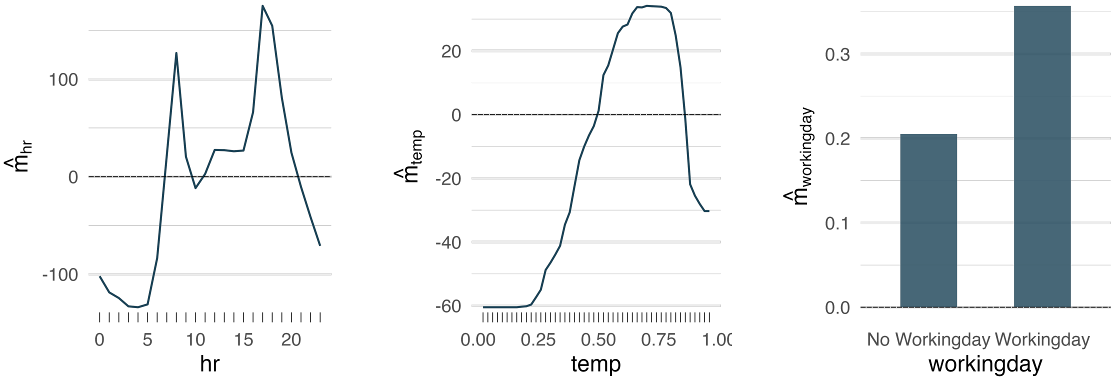
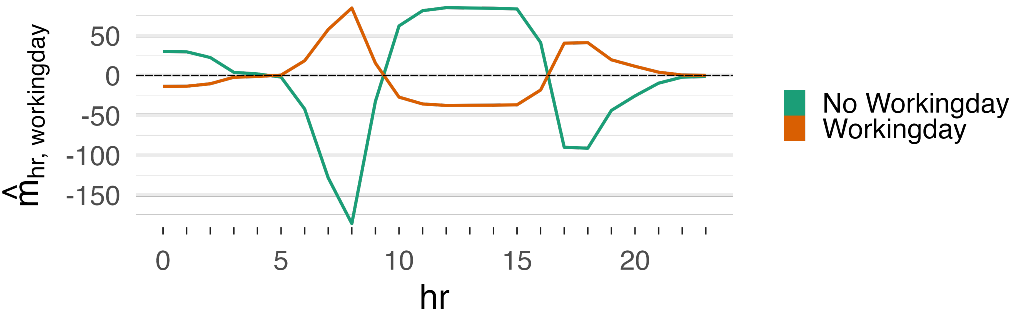


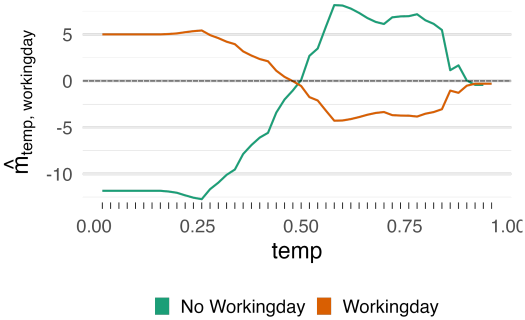
$$\hat{m} = \hat{m}_0 + \hat{m}_{\mathtt{hr}}(\mathtt{hr}) + \hat{m}_{\mathtt{temp}}(\mathtt{temp}) + \hat{m}_{\mathtt{workingday}}(\mathtt{workingday}) + \dots$$

Hour × Working Day: "Rush Hour Effect"



$$\ldots + \hat{m}_{\texttt{hr,workingday}}(\texttt{hr}, \texttt{workingday}) + \ldots$$

More 2nd Order Interactions



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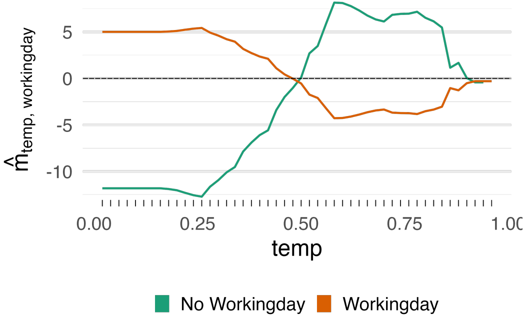
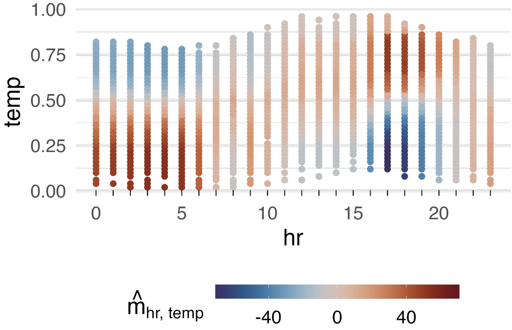
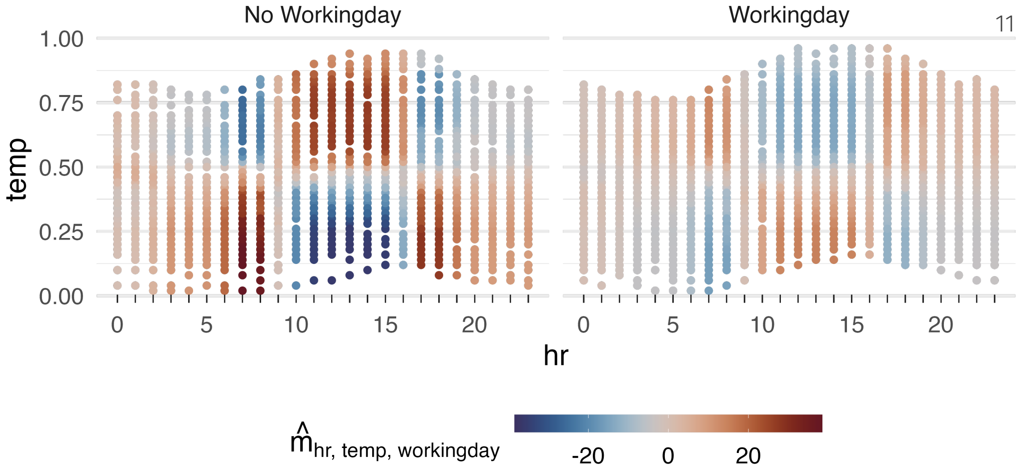




$$+\hat{m}_{\texttt{temp,workingday}}(\texttt{temp}, \texttt{workingday}) \qquad +\hat{m}_{\texttt{hr,temp}}(\texttt{hr}, \texttt{temp}) + \ldots$$

3rd Order Interaction



Feature Importance in RPF

- Average of absolute values of term $\hat{m}_S$ of interest

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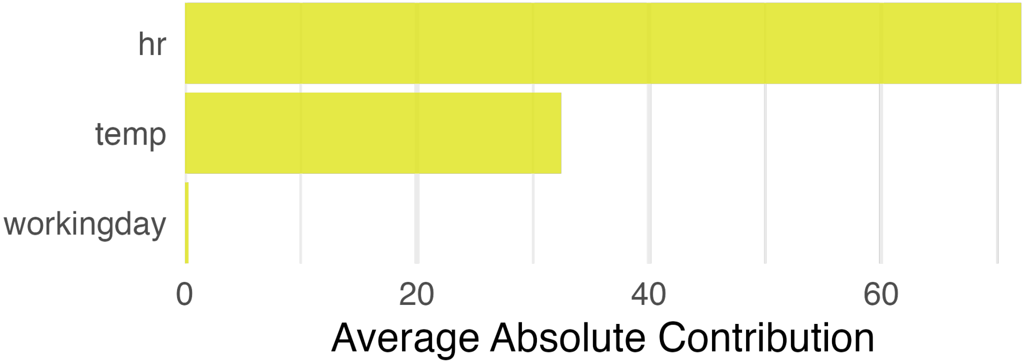
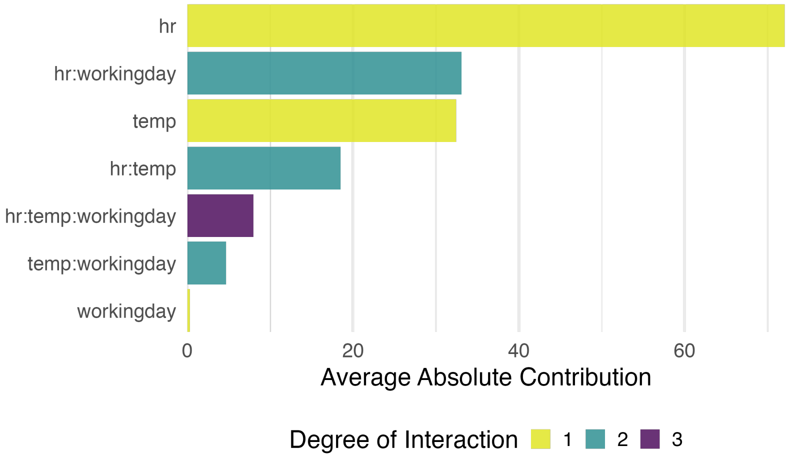
  - Importance scores on same scale as prediction

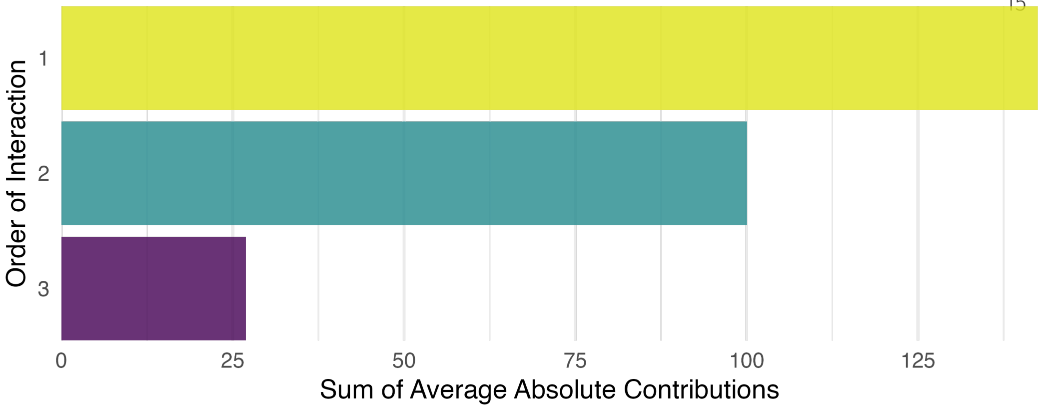
Feature Importance per Main Term



Feature Importance for All Terms



Feature Importance by Order of Interaction



No Free Lunch

Gains in interpretibility → sacrifices in predictive performance?

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→ Generally: RPF never best, rarely bad, usually close

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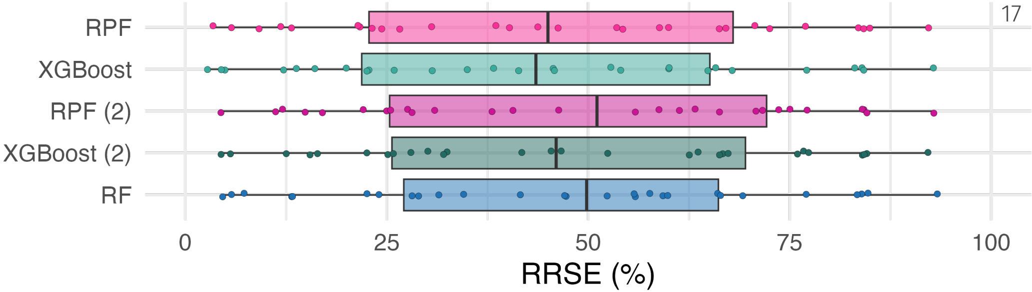
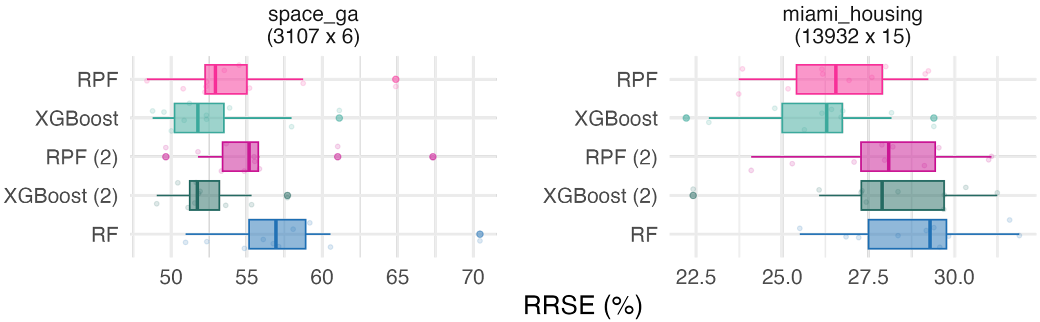
Benchmark Results (Aggregated)



$$\mathrm{RRSE} := \sqrt{\mathrm{SSE}(Y, \hat{Y}) \;/\; \mathrm{SSE}(Y, \bar{Y})}$$

→ Featureless model scores 1, perfect score 0

Benchmark Results (Selected Tasks)



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- (↑) R package available [3]
- (→) Competetive predictive performance (mostly)
- (↓) Computationally heavy for large data (Optimization WIP!)

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Thank you for your attention!

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References I

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