Random Planted Forest: A Directly Interpretable Tree Ensemble

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Motivation

- Tree-based methods like Random Forest (RF):

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

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\hat{m}(\mathbf{x}_i) = &\hat{m}_0 + \\
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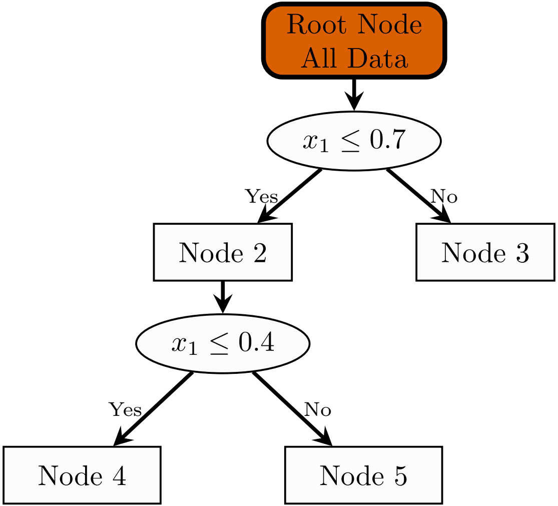
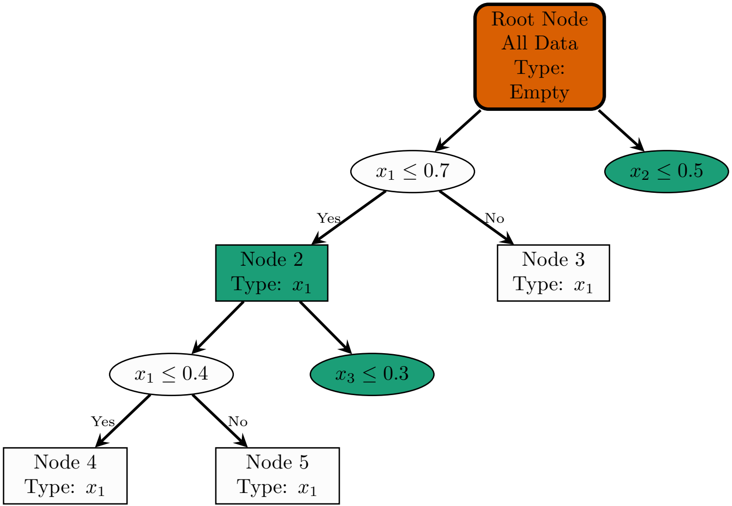
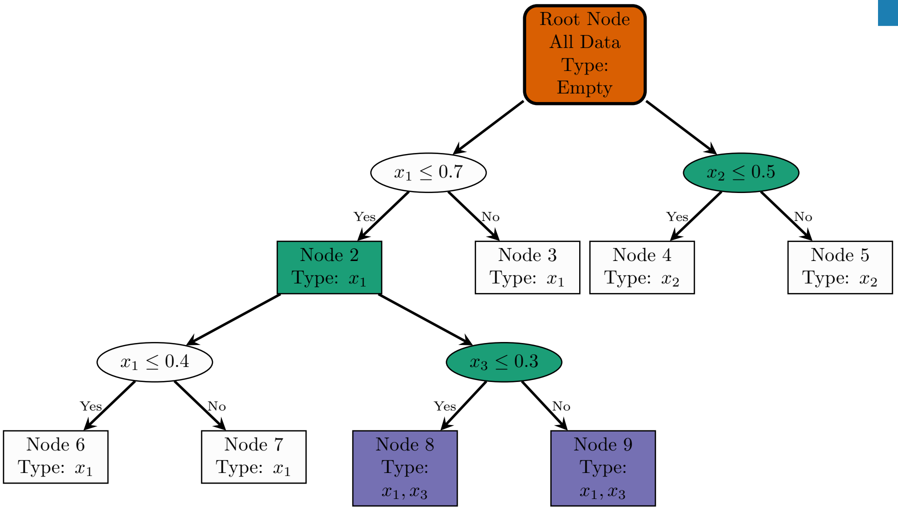
Trees in Random Forest



Planted Trees (I)



Planted Trees (II)



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- Prediction built incrementally using residuals (cf. Gradient Boosting)
- Tree stops after adjustable number of splits

Application Example

- `Bikeshare` regression dataset [1]

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

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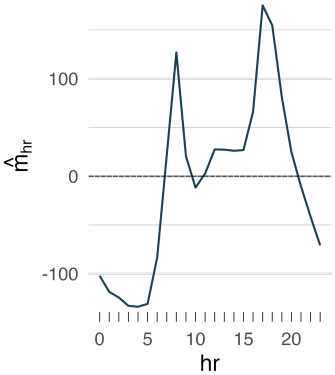
Main Effects



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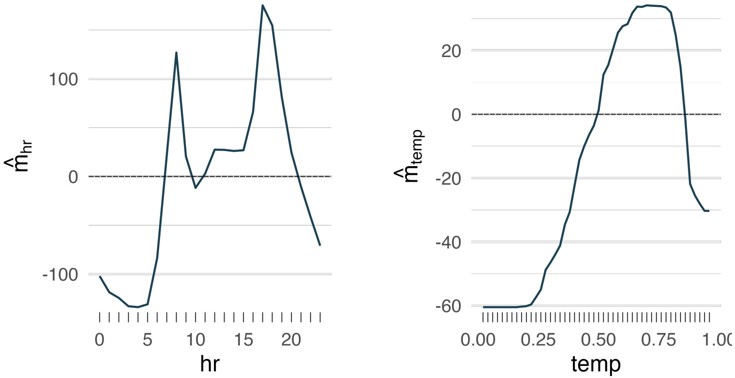

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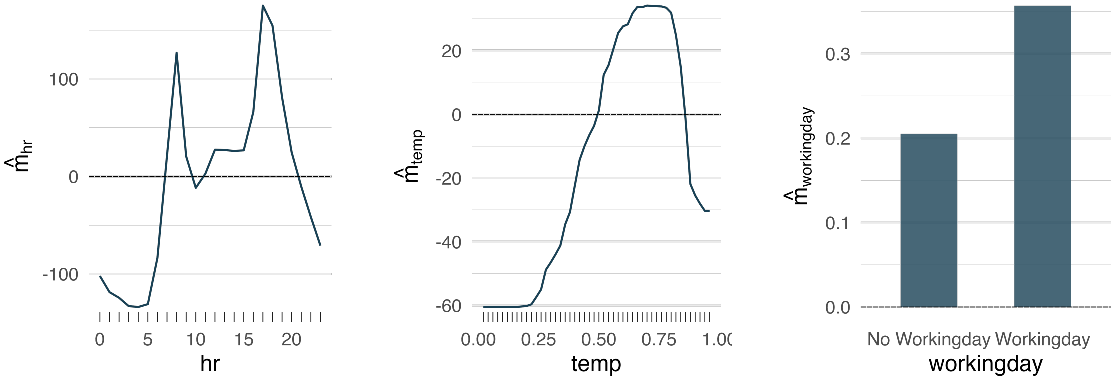
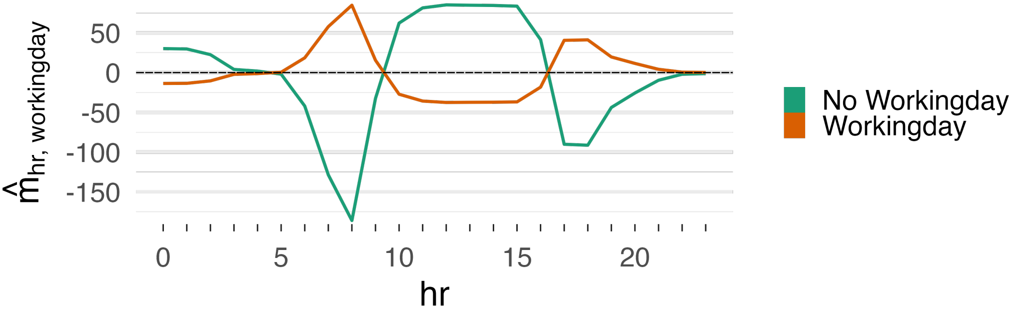


$$\hat{m} = \hat{m}_0 + \hat{m}_{\mathtt{hr}}(\mathtt{hr}) + \hat{m}_{\mathtt{temp}}(\mathtt{temp}) + \hat{m}_{\mathtt{workingday}}(\mathtt{workingday}) + \ldots$$

Hour × Working Day: "Rush Hour Effect"



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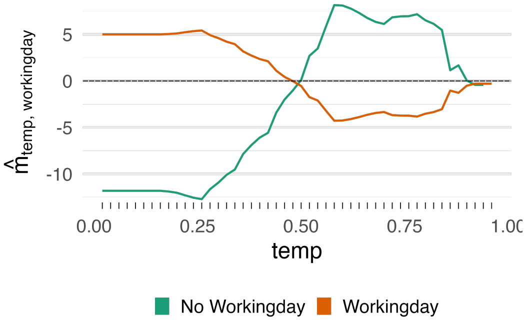
More 2nd Order Interactions



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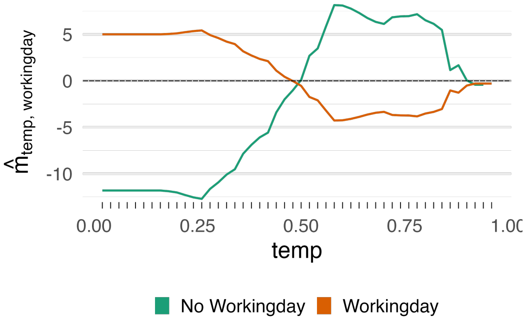

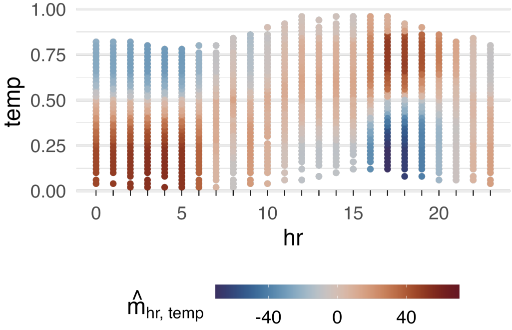

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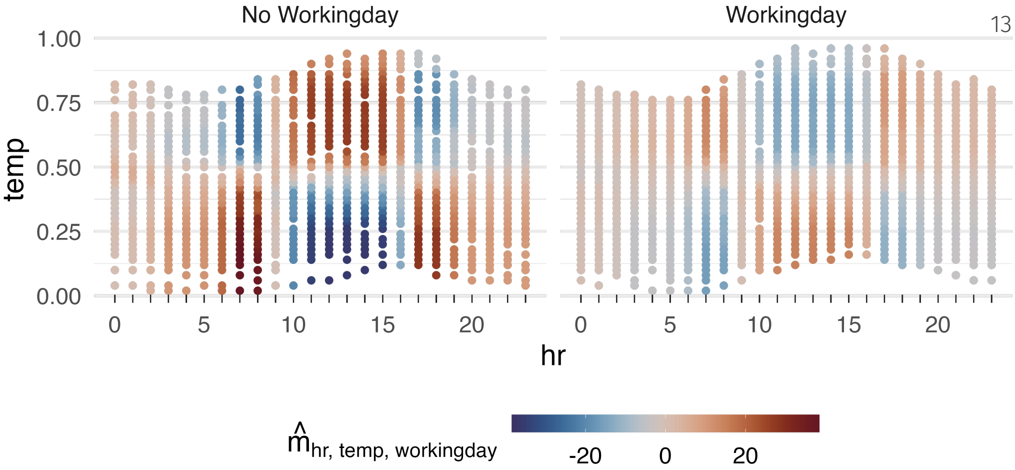
3rd Order Interaction



Feature Importance in RPF

$$\mathrm{FI}_S = \frac{1}{n} \sum_{i=1}^{n} |\hat{m}_S(\mathbf{x}_i)|$$

- Average of absolute terms $\hat{m}_S$ for S of interest

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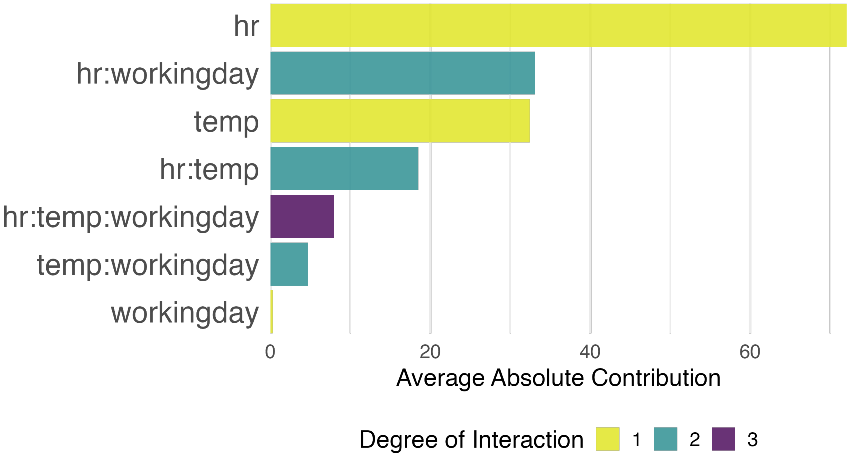
- Scores also per interaction term
- Importance scores on same scale as prediction

Feature Importance: All Terms



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- RPF slower (especially with large data)

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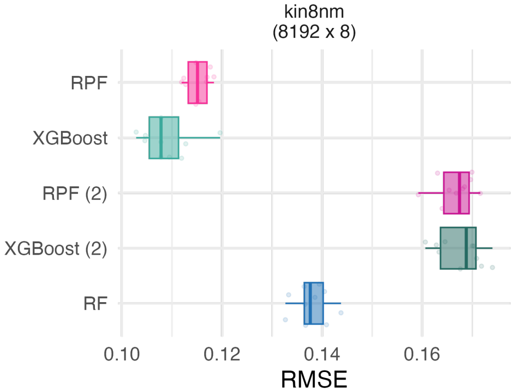
Benchmark Results (Selected Tasks)



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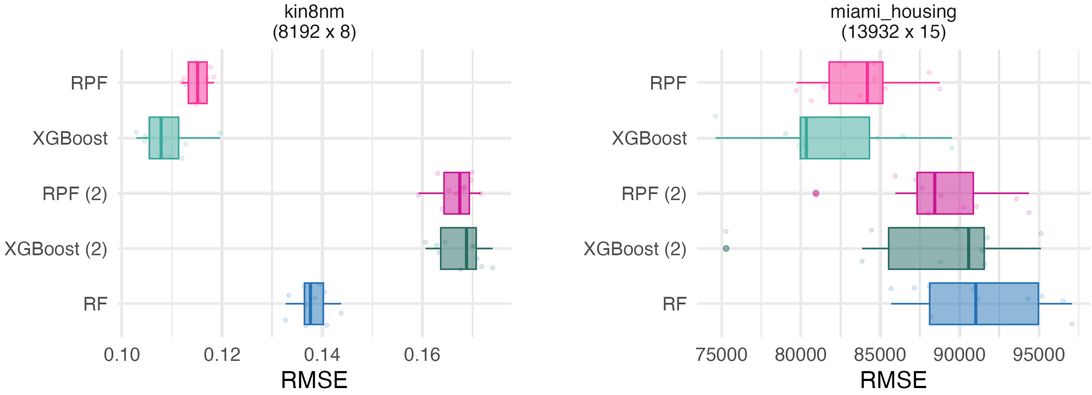

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- ($\downarrow$) Slower for large data (Optimization WIP!)

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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).