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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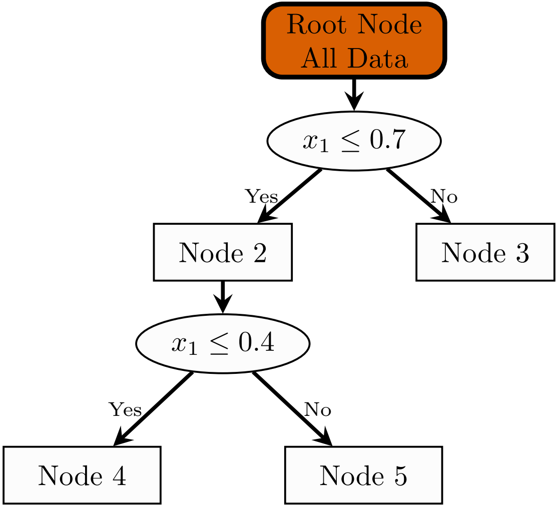
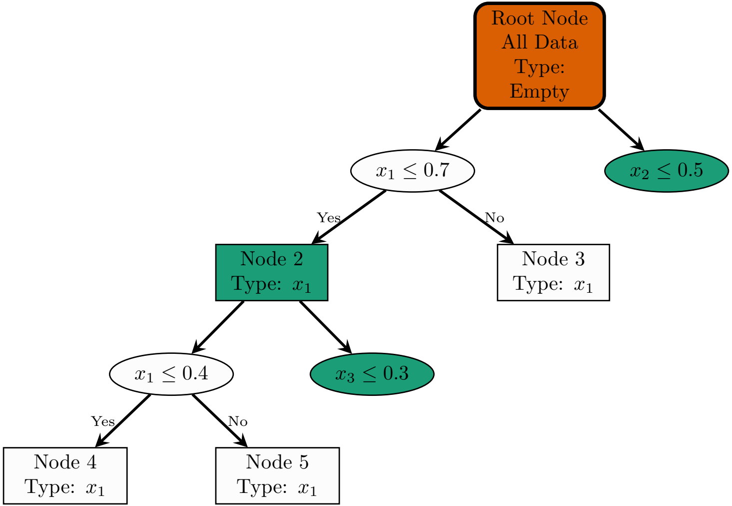
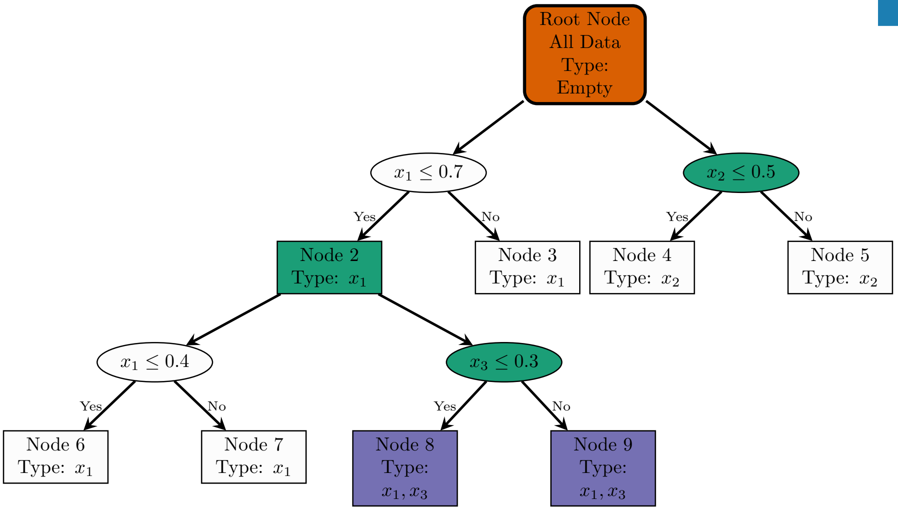
Trees in Random Forest



Planted Trees (I)



Planted Trees (II)



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- Degree of interaction can be constrained
- Tree stops after adjustable number of splits
- Prediction built up incrementally using residuals (cf. Gradient Boosting)

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- `Bikeshare` regression dataset [1]

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  - `workingday` binary → {`workingday`, `no workingday`}
- Average prediction: $\hat{m}_0 \approx 144$

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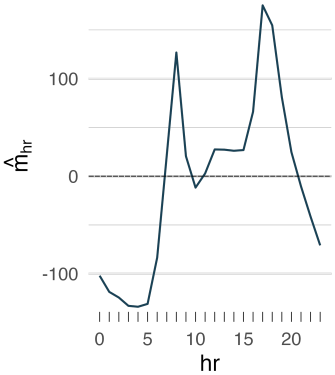
Main Effects



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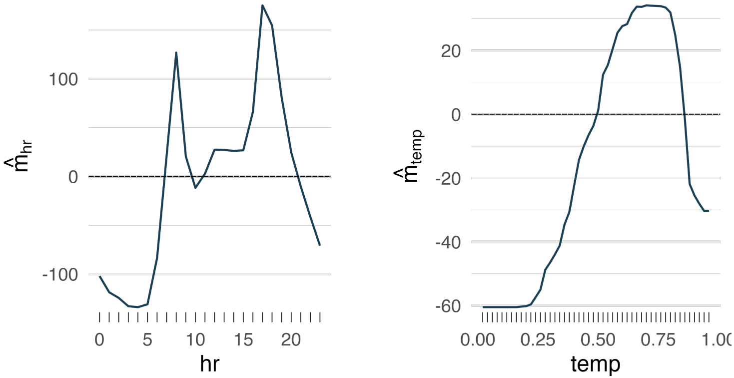

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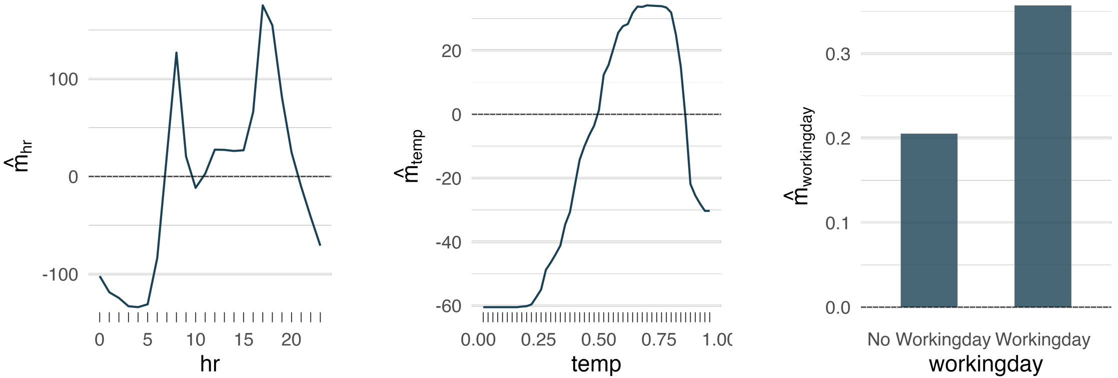

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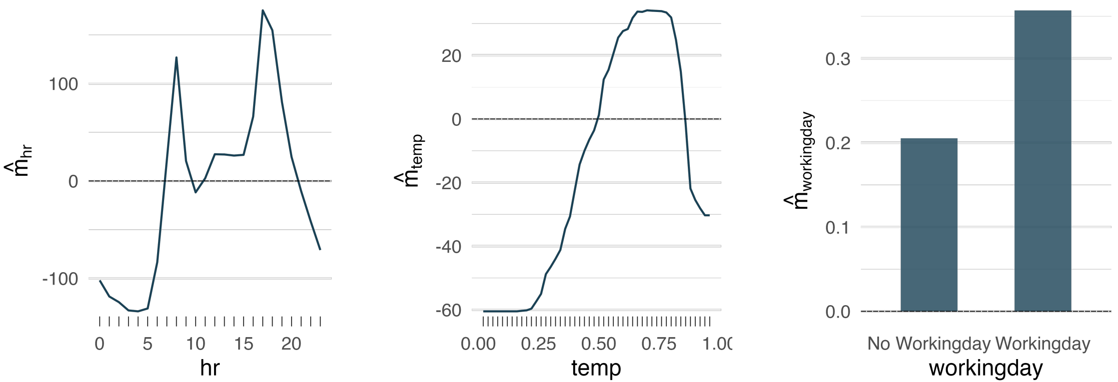
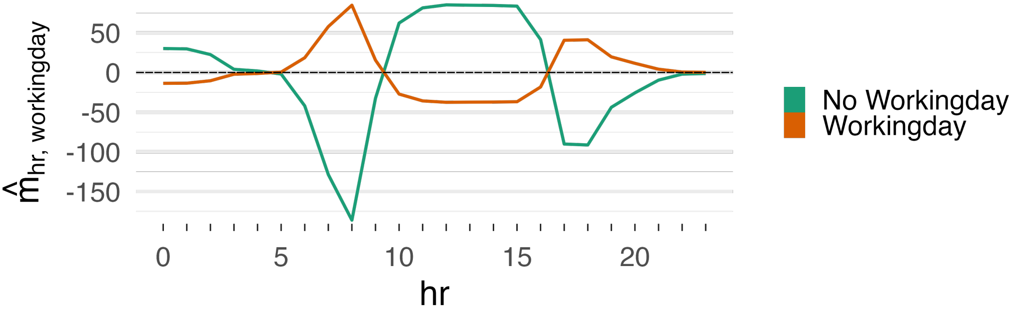


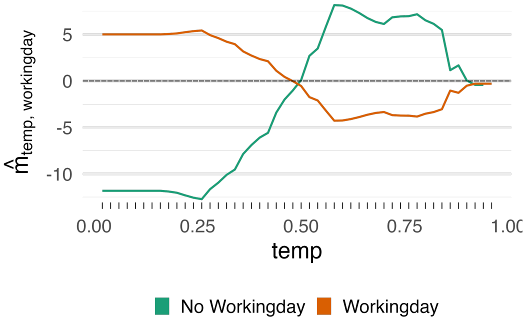
$$\hat{m} = \hat{m}_0 + \hat{m}_{\texttt{hr}}(\texttt{hr}) + \hat{m}_{\texttt{temp}}(\texttt{temp}) + \hat{m}_{\texttt{workingday}}(\texttt{workingday}) + \dots$$

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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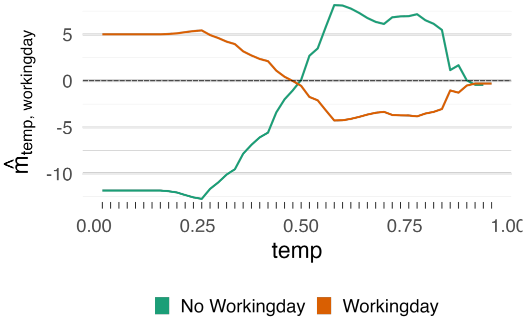
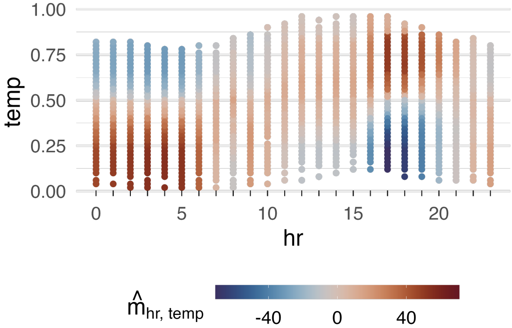
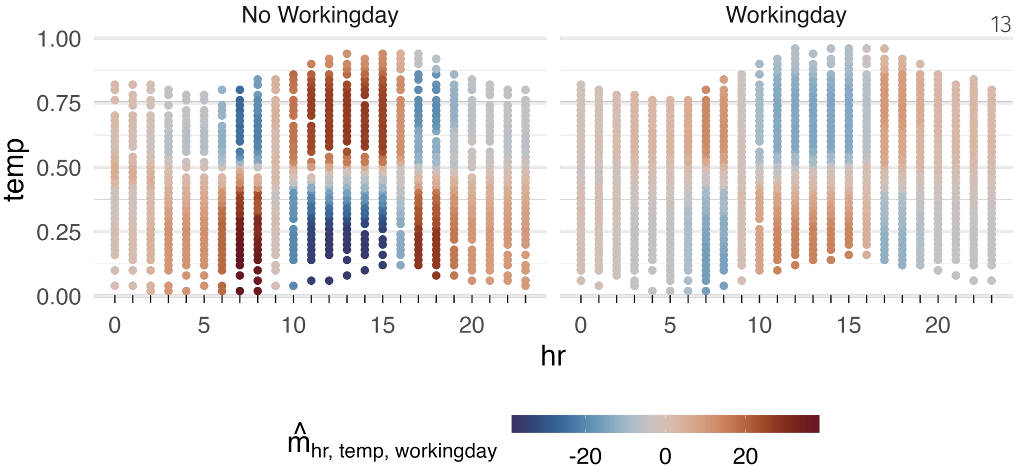




$$+\hat{m}_{\texttt{temp,workingday}}(\texttt{temp}, \texttt{workingday}) \qquad +\hat{m}_{\texttt{hr,temp}}(\texttt{hr}, \texttt{temp}) + \ldots$$

3rd Order Interaction



Feature Importance in RPF

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

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

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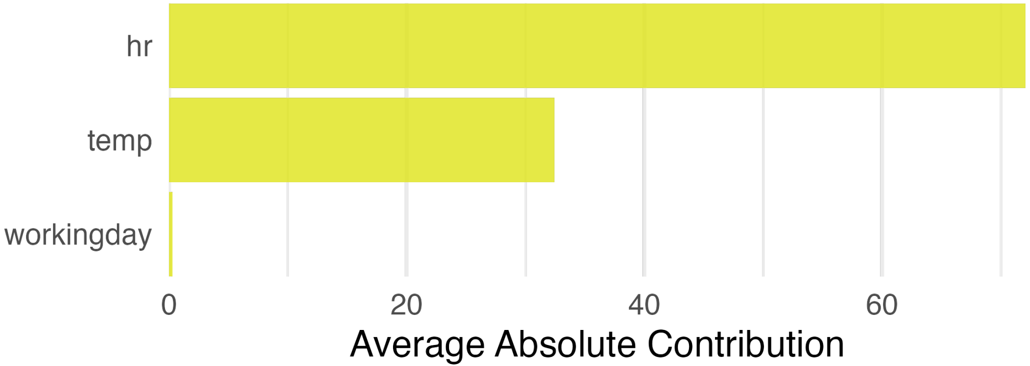
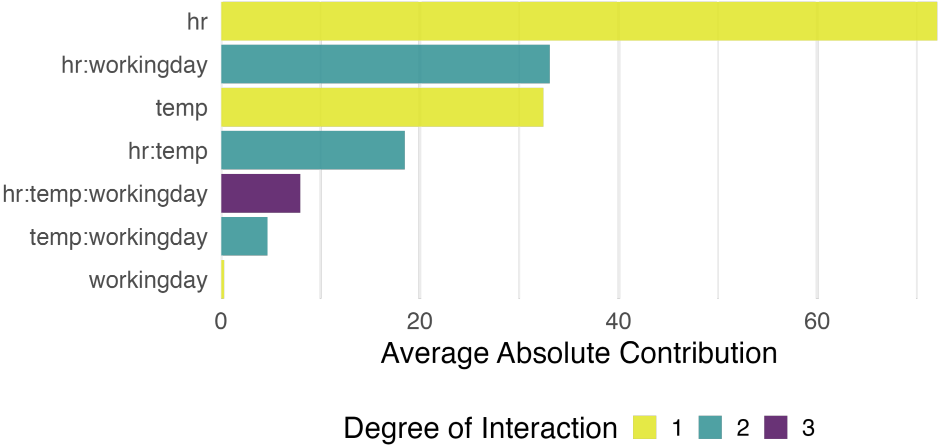
  - Importance scores on same scale as prediction

Feature Importance: Main Terms



Feature Importance: All Terms



No Free Lunch

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

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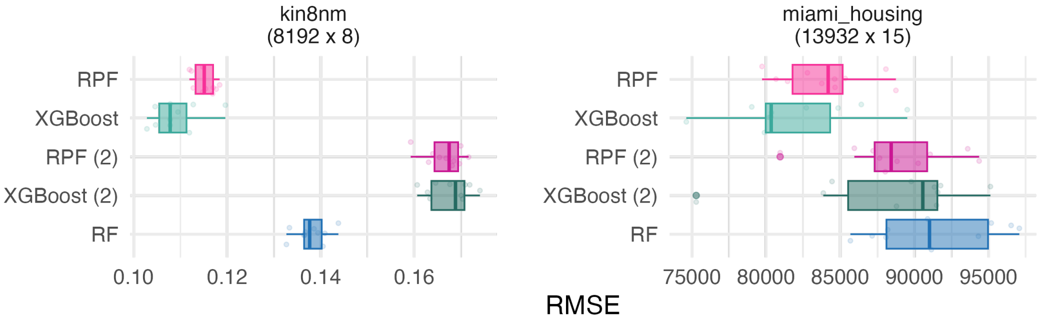
Benchmark Results (Selected Tasks)



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- (↑) Quantifies main effects and interaction terms
- (↑) 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).