

# DOF: Optimized Personalization of Multi-Armed Treatment Assignment in R and C++

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## Summary

The problem of learning the assignment of treatments is omnipresent in economics and public health. It arises, for example, from randomized controlled trials where a variety of behavioral nudges (treatments) are developed to enhance vaccination uptake against coronavirus disease 2019 (COVID-19) or influenza, especially among racially or ethnically underrepresented and socioeconomically disadvantaged populations (Milkman et al. 2021, 2022; Dai et al. 2021). Subject-specific covariates containing information regarding sociodemographics, clinical characteristics, and comorbid conditions, if available, can be harnessed to identify personalized treatment assignment schemes. The DOF package provides a user-friendly implementation of the direct optimization forest (DOF), a forest-based treatment assignment algorithm featuring greedy recursive partitioning (Athey, Tibshirani, and Wager 2019), treatment and covariate resampling in bootstrap tree aggregating (Breiman 1996), outcome residualization and regularization, and k-means treatment clustering (Hartigan and Wong 1979). Personalized treatment learning is achieved through optimizing a regularized empirical analogue of the expected outcome. The integration of R (R Core Team 2022) and C++ (Stroustrup 2013) substantially boosts the computational efficiency in tree partitioning and aggregating. This package is especially suitable in randomized controlled trial settings where a large number of treatment arms are present.

## Statement of Need

There is an ever-growing literature in the intersection of machine learning and causal inference attempting to address the problem of optimal treatment assignment through heterogeneous treatment effect estimation (Athey and Imbens 2016; Wager and Athey 2018; Hitsch and Misra 2018; Athey, Tibshirani, and Wager 2019; Sverdrup et al. 2020; Athey and Wager 2021). Other methods focus on maximizing the benefit (empirical welfare) from treatment assignment (e.g., Kitagawa and Tetenov 2018), or the chance of assigning an individual to an optimal treatment arm (e.g., Murphy 2005; Zhou, Wang, and Zeng 2018). Most of these methods perform well with a limited number of treatment and control groups. As more arms are present, the estimation of arm-specific empirical welfare and the identification of individual-specific optimal arms become increasingly difficult. Commonly used implementations such as the multi-armed causal forest (Tibshirani et al. 2022) and random forest (Wright and Ziegler 2017) lead to significantly suboptimal assignment with insufficient levels of empirical welfare, whereas the DOF yields elevated welfare, closer to an optimal level from the oracle assignment (simulation results available in Figure 1). This advantage of DOF over existing approaches justifies our software development endeavors. Moreover, incorporating recursive tree partitioning and aggregating, the DOF has a high level of methodological and computational complexity. Customized implementation hence requires a

- software engineering challenge/computing

## Mathematics

Single dollars (\$) are required for inline mathematics e.g.  $f(x) = e^{\pi/x}$

Double dollars make self-standing equations:

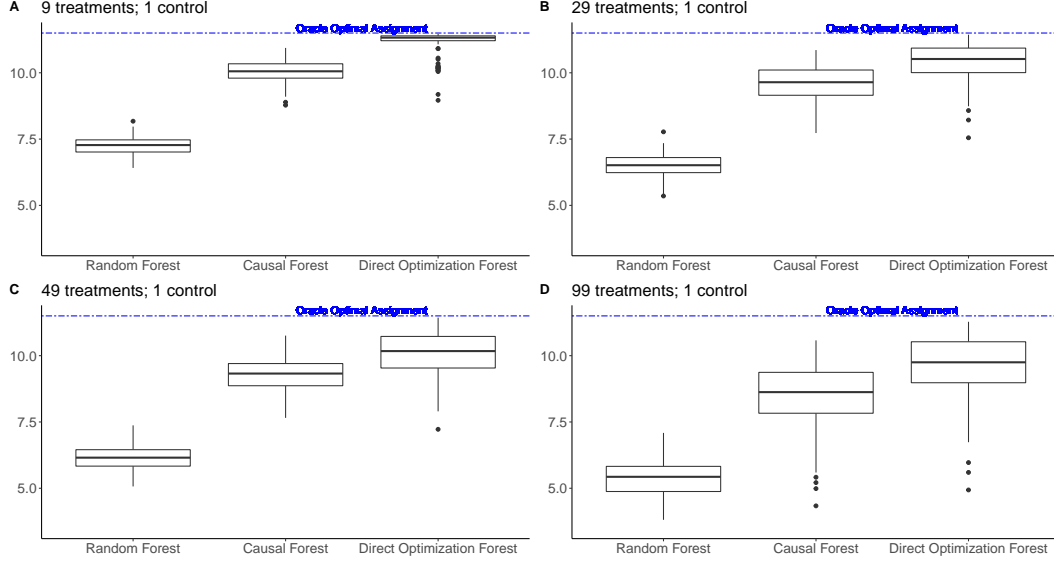


Figure 1: Direct optimization forest, random forest, and multi-armed causal forest with an increasing number of treatment arms.

$$\Theta(x) = \begin{cases} 0 & \text{if } x < 0 \\ 1 & \text{else} \end{cases}$$

You can also use plain L<sup>A</sup>T<sub>E</sub>X for equations

$$\hat{f}(\omega) = \int_{-\infty}^{\infty} f(x)e^{i\omega x} dx \quad (1)$$

and refer to Equation 1 from text.

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