

# MISQ Archivist

## A Prescriptive Analytics Framework for Optimal Policy Deployment Using Heterogeneous Treatment Effects

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### Abstract

We define a prescriptive analytics framework that addresses the needs of a constrained decision-maker facing, *ex ante*, unknown costs and benefits of multiple policy levers. The framework is general in nature and can be deployed in any utility maximizing context, public or private. It relies on randomized field experiments for causal inference, machine learning for estimating heterogeneous treatment effects, and the optimization of an integer linear program for converting predictions into decisions. The net result is the discovery of individual-level targeting of policy interventions to maximize overall utility under a budget constraint. The framework is set in the context of the four pillars of analytics and is especially valuable for companies that already have an existing practice of running A/B tests. The key contribution in this work is to develop and operationalize a framework to exploit both within- and between-treatment arm heterogeneity in the utility response function, in order to derive benefits from future (optimized) prescriptions. We demonstrate the value of this framework as compared to benchmark practices (i.e., the use of the average treatment effect, uplift modeling, as well as an extension to contextual bandits) in two different settings. Unlike these standard approaches, our framework is able to recognize, adapt to, and exploit the (potential) presence of different subpopulations that experience varying costs and benefits within a treatment arm, while also exhibiting differential costs and benefits across treatment arms. As a result, we find a targeting strategy that produces an order of magnitude improvement in expected total utility, for the case where significant within- and between-treatment arm heterogeneity exists.

**Keywords:** Prescriptive analytics, heterogeneous treatment effects, optimization, observed utility rank condition (OUR), between-treatment heterogeneity