OPTIMAL COMPREHENSIBLE TARGETING

ABSTRACT:

Developments in machine learning and big data allow firms to fully personalize and target their marketing mix. However, data and privacy regulations, such as those in the European Union (GDPR), incorporate a “right to explanation”, which is fulfilled when targeting policies are comprehensible to customers. This paper provides a framework for firms to navigate right to explanation laws. First, I introduce a new method called Policy DNN, which combines policy learning and deep neural networks, to form a profit-maximizing black box benchmark and provide theoretical guarantees on its performance. In contrast to prior approaches that use a two-step method of estimating treatment effects before assigning individuals their treatment group, Policy DNN directly estimates treatment assignment, which improves efficiency.

Second, I construct a class of comprehensible targeting policies that is represented by a sentence. Third, I show how to optimize over this class of policies to find the profit maximizing comprehensible policy. I demonstrate that it is optimal to estimate the comprehensible policy directly from the data, rather than projecting down the black box policy into a comprehensible policy. Finally, I apply my framework empirically in the context of price promotions for a durable goods retailer using data from a field experiment. I quantify the cost of explanation, which I define as the difference in expected profits between the optimal black box and comprehensible targeting policies. The comprehensible targeting policy reduces profits by 7% or 22 cents per customer when compared to the black box benchmark.