UNIVERSITY of HOUSTON | ENGINEERING

Department of Industrial Engineering

Monday, August 2, 2021

10:00 AM – 12:00 PM CDT

Zoom link: https://uh-edu-cougarnet.zoom.us/j/97386040644?pwd=RWgrV01iNDZibStHdHA3WFdwNzY3UT09

Meeting ID: 973 8604 0644

Passcode: 738541

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Ph.D. Dissertation Defense

Advisor: Taewoo Lee

"Data-Driven Inverse Linear Programming: Integrating Inverse Optimization and Machine Learning"

Abstract

Given a set of observed decisions, the goal of inverse optimization (IO) is to infer the unknown parameters of a "forward" optimization problem. These parameters usually represent the decision-maker's preferences and can be used to solve the forward optimization problem and find optimal solutions close to the observed decisions. Among different types of IO models, inverse linear programming (LP) has received increasing attention due to its potential to infer efficient optimization formulations that can closely replicate or predict the behavior of a complex decision-making system. In this thesis, we integrate data-driven IO techniques with ideas from statistical machine learning to improve the stability and applicability of IO in settings that involve imperfect data and observations from decision makers with different preferences.

First, we discuss the sensitivity of the inversely inferred parameters and corresponding forward solutions from the existing inverse LP methods to noise, errors, and uncertainty in the input data. We then introduce the notion of inverse and forward stability in inverse LP and borrow ideas from quantile regression to propose a novel inverse LP method that is more stable under data imperfection. We formulate the inverse model as a tractable large-scale mixed-integer program (MIP) and apply it to diet survey data to recommend diets that are consistent with the individual's food preferences. Second, we analyze the complexity of the quantile-based MIP formulation and elucidate its connection to biclique problems, which we exploit to develop an exact algorithm and heuristics that solve much smaller MIPs instead to construct a solution to the original problem. Finally, we integrate inverse optimization and clustering and propose a new clustering approach, called optimality-based clustering, which clusters the data points based on their encoded decision preferences. We assume that each data point is a decision made by a rational decision maker (i.e., by approximately solving an optimization problem), and cluster the data points by identifying a common objective function of the optimization problems for each cluster such that the worst-case optimality gap for the data points within each cluster is minimized.