Given the increasing usage of automated prediction systems in the context of high-stakes decisions, a growing body of research focuses on tools and methods for detecting and mitigating biases and unfairness in algorithmic decision-making. A particularly promising post-processing method, Multiaccuracy-Boost, has been proposed by Kim et al. (2019), adapting the multicalibration framework of Hébert-Johnson et al. (2018). The underlying fairness notion, multiaccuracy, promotes the idea of subgroup fairness and requires accurate predictions not only for marginal populations, but also for subpopulations that may be defined by complex intersections of many attributes.

In this project, we aim at extending and applying the multiaccuracy framework to tackle (1) the problem of adapting a prediction model to a new distribution under covariate shift and (2) the challenge of deriving unbiased estimates from nonprobability samples. In both cases, post-processing for multiaccuracy can help to robustify a prediction model against distributional shifts and to maintain good performance on the new domain. We combine the computer science and survey science perspective on both problems to highlight and utilize the similarities between the multiaccuracy framework, adaptation under covariate shift and inference based on nonprobability samples.