Doubly robust estimators are a popular means of estimating causal effects. Such estimators combine an estimate of the conditional mean of the study outcome given treatment and confounders (the so-called outcome regression) with an estimate of the conditional probability of treatment given confounders (the propensity score) to generate an estimate of the effect of interest. This estimate is consistent so long as at least one of these two regressions is consistently estimated. It turns out that doubly robust estimators are often statistically efficient, achieving the lower bound on the variance of regular, asymptotically linear estimators. However, in spite of their asymptotic optimality, in problems where estimands are weakly identified, doubly robust estimators may behave erratically. We propose a new framework for inference in these challenging settings. We introduce the idea of collaborative asymptotically linear estimators. These estimators use doubly robust frameworks; however, rather than using an estimate of the propensity score, they opt for an alternative quantity with reduced dimension relative to the true propensity score. In this talk, I’ll discuss these issues in the context of estimating the causal effect of a binary treatment on an outcome. Pending time and wakefulness of the audience, I will discuss extensions to a general setting where the observed data are the result of a conditionally random coarsening of a full data structure.