Yakov Ben-Haim and Mike Smithson, Data-Based Prediction under Uncertainty: A Dual Approach. *Journal of Mathematical Psychology,* to appear.

Abstract Data underlie understanding of processes and prediction of the future. However, things change; data from one population at one time may have uncertain relevance for modeling or prediction in another population or at another time. Data-based prediction in a changing world requires two complementary capabilities: versatile modeling, integrated with management of uncertainty. We develop a response to this challenge. We focus on statistical models of bounded random variables, associated with additional non-probabilistic uncertainties. We employ CDF-quantile distributions to model the probabilistic aspects of these phenomena. Non-probabilistic uncertainties in parameter values and in the shapes of probability distributions are modeled and managed with the method of robust satisficing from info-gap theory. The robustness to uncertainty is evaluated for alternative estimators. We show that putatively optimal estimators may be less robust than sub-optimal estimators, suggesting preference for a sub-optimal estimator in some circumstances. These two attributes — statistical accuracy and info-gap robustness — trade off against one another. The info-gap robustness function quantifies this trade off. Generic propositions specify the robustness functions and their trade offs, and characterize a class of situations in which preference for sub-optimal estimators can occur. Three examples are discussed.

Keywords probabilistic prediction; non-probabilistic uncertainty; data-based modeling; CDF-quantile distributions; info-gap theory; robustness

Highlights

- Data-based modeling and prediction of quantile ranks.
- CDF-quantile distributions for modeling bounded random variables.
- Info-gap theory and robustness to non-probabilistic uncertainty.
- Tradeoff of statistical accuracy against robustness to non-probabilistic uncertainty.

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