Abstract: Estimation is a ubiquitous problem in almost all fields of engineering, which typically involves 3 elements, i.e. model, algorithm, and data. While substantial efforts have been devoted to model development and algorithm design, our interest focuses on exploring the role of data in estimation, e.g. what are the optimal data that would yield the best estimation accuracy? Traditionally, a “gold standard” for evaluating and optimizing the quality of data is the sensitivity-based Fisher information, which however, is subject to highly restrictive assumptions and suffers major limitations including inability to address system uncertainties. We have recently discovered certain data structures that relate estimation errors to system uncertainties. By incorporating these data structures for data optimization, it is shown that the accuracy of estimation can be dramatically improved under system uncertainties (by up to 1 order of magnitude). Based on these data structures, we are developing a new set of criteria and framework applicable to a variety of data-optimization-for-estimation problems, including optimal experiment design for system identification, data selection/mining (from passive data stream) for online estimation, parameter management, and sensor (re)configuration.

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