1154-60-1576 **Mauro Maggioni*** (`mauro@math.jhu.edu`), 3400 N Charles St, Department of Mathematics, Baltiomre, MD 21218, and **Fei Lu**, **Jason Miller**, **Sui Tang** and **Ming Zhong**. *Learning Interaction laws in particle- and agent-based systems.*

We consider the following inference problem for a system of interacting particles or agents: given only observed trajectories of the system, we are interested in estimating the interaction laws between the particles/agents. We consider both the mean-field limit (i.e. the number of particles going to infinity) and the case of a finite number of agents, with an increasing number of observations; in this talk we will mostly focus on the latter. We show that at least in the particular setting where the interaction is governed by an (unknown) function of pairwise distances, under a suitable coercivity condition that guarantees the well-posedness of the problem of recovering the interaction kernel, statistically and computationally efficient, nonparametric, suitably-regularized least-squares estimators exist. Our estimators achieve the optimal learning rate for one-dimensional (the variable being pairwise distance) regression problems with noisy observations. We discuss several examples, including extensions to agent systems with different types of agents, second-order systems, and families of systems with parametric interaction kernels. We also conduct numerical experiments to test the large time behavior of these systems, especially in the cases where they exhibit emergent behavior. (Received September 16, 2019)