LEARNING AND INFLUENCE IN NETWORKS

BENJAMIN GOLUB

Abstract. Consider people repeatedly learning from each over time in a network of relationships. Is dispersed information aggregated efficiently? Whose opinions or experiences are particularly influential? How does the interplay between the structure of the network and the structure of information determine the answers? We begin with a quick but self-contained review of classic results characterizing when agents reach consensus [2, 10, 18, 19, 17] and relate this to both the herding literature [4, 21, 1] and martingale theory. We conclude this part with some recent breakthroughs [15, 16] that give general and powerful ways of analyzing when the consensus aggregates information efficiently.

Unfortunately, the classic models have less to say about who is influential, about what learning is like when it is imperfect, about the causes of disagreement, and about the rate of convergence. We next turn to a literature in behavioral learning on networks which answers these questions under certain non-Bayesian behavioral learning rules, most prominently that of DeGroot [6]. We briefly survey the key techniques of this approach, which use algebraic statistics of a social network to characterize outcomes such as the accuracy and polarization of social learning outcomes [7, 22, 11, 12, 13]. This approach raises questions about foundations of non-Bayesian learning rules in networks [14] and relates to studies of influence in networks more generally [3, 9].

In the last lecture, we turn to recent work that aims to obtain models as tractable as the behavioral ones just discussed, but with Bayesian foundations. For this, it turns out to be helpful to work with learning environments that are stationary, in contrast to most of the prior work [8, 20]. We demonstrate how this can be used to give a tractable description of influence in a social learning equilibrium, as well as new sorts of answers to the question of when learning is efficient [5].

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Department of Economics, Harvard University.

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