Doctoral Final Defense

Bayesian-robust Algorithms Analysis with Applications in Mechanism Design

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Location: Mudd 3514

Abstract:

This thesis studies Bayesian-robustness of algorithm design. In the prior independent setting, inputs are independent and identical draws (i.i.d.) from an unknown Bayesian distribution which is an element of a known, large class of distributions. An algorithm's performance is measured in worst-case over distributions as approximation against the optimal algorithm which knows the distribution.

This thesis gives a method -- the Blends Technique -- that is agnostic to algorithm problem setting for proving lower bounds on prior independent approximation, i.e., the method establishes a fundamental limit on how good the best prior independent algorithm is. The method constructs a correlated distribution over inputs that can be generated both as a distribution over i.i.d good-for-algorithms distributions and as a distribution over i.i.d. bad-for-algorithms distributions. The ratio of the expected performances of the Bayesian optimal algorithms for these two decompositions is a lower bound on the prior independent approximation ratio. This framework is applied to give novel lower bounds on canonical prior independent mechanism design problems.

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Committee Members:

Dr. Jason Hartline	Computer Science, Committee Chair
Dr. Aravindan Vijayaraghavan	Computer Science
Dr. Denis Nekipelov	Virginia Economics

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Zoom meeting information:
https://northwestern.zoom.us/j/99848874341

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This thesis further uses the perspective of Bayesian-robustness to inform benchmark design for the prior free information setting (i.e., worst-case over inputs / competitive analysis). Benchmark functions are free parameters and choice of benchmark is material. This thesis gives a framework for optimal benchmark design from a requirement that approximation of a prior free benchmark must further hold as a prior independent approximation guarantee. Subsequently, it shows that benchmark design from this framework is equivalent to optimal prior independent algorithm design. Additionally, this thesis solves a central open question in prior independent mechanism design, namely it identifies the prior independent revenue-optimal mechanism for selling a single item to two agents with i.i.d. values from a regular distribution. As a corollary, this optimal mechanism is used to solve the corresponding benchmark design problem.