Doctoral Final Defense

Bayesian-robust Algorithms Analysis with Applications in Mechanism Design

Aleck Johnsen

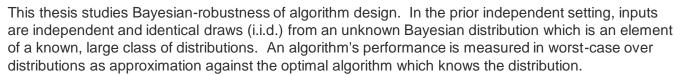
PhD Candidate

Computer Science, Northwestern University

July 30, 2021 • 1:00 PM (CT)

Location: Mudd 3514

Abstract:



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

If you'd like to attend Aleck Johnsen's presentation via zoom, please use the following link: Zoom meeting information:

https://northwestern.zoom.us/j/99848874341



Complete 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.

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.