Research Statement *Michail G. Lagoudakis*

In my research I effectively use computers to solve challenging decision-making and control problems. In particular, I focus on developing general tools that enable a machine to learn a solution adaptively. This is a far superior method to executing a hand-coded solution, because most of the problems we face today contain not only complex and stochastic dynamics, but also uncertainty about the dynamics itself, and thus do not admit static off-line solutions.

I build on the strength of the current computer technology to manipulate numbers and complex data structures extremely quickly. In extracting statistics from huge data sets, evaluating complex functions, and solving large systems of equations, machines routinely outperform people. I am exploiting this computational power in conjunction with solid statistical methods to provide a basis for handling the inherent uncertainty and nondeterminism that characterizes most outstanding decision-making problems.

In joint work with Michael Littman at Duke and AT&T Labs, I focused on learning methods for the algorithm selection problem (adaptively and recursively choosing the appropriate algorithm for each incoming problem instance). Eventually, I came to realize that there is need for more efficient and powerful reinforcement-learning methods, so during my Ph.D. work with Ronald Parr at Duke, I focused on general-purpose reinforcement-learning algorithms with goals in two directions: efficient utilization of data and scaling to large problems. I used techniques from linear algebra, function approximation, linear programming, monte-carlo estimation, and pattern recognition to devise and propose learning algorithms that meet the challenges of a wide range of decision making problems.

I am currently doing research in this area at Georgia Tech and apply my methods to industrial problems (disassembly planning, routing in re-entrant lines) and coordination problems (multi–robot tasks). In the near future, I plan to continue on problems from operations research (economic markets and auctions, scheduling), networking (dynamic packet routing, router/server reconfiguration), and meta–computation (using learning and reasoning to build "smarter" computers that make better use of their resources, as opposed to simply faster computers). During this process, I expect to raise more fundamental and/or theoretical questions. In parallel, I collaborate with medical doctors from Emory University on supervised learning methods for computer-aided diagnosis of gastrointestinal bleeding.

In the past, I have established a solid basis in neural systems (Hopfield networks, neural maps), robotics (path planning, motion control), human-computer interaction (speech interfaces), and DNA computation (self–assembly). I still maintain a strong interest in all these fields and I am actively seeking collaborations along these lines.

My long-term vision is two-fold and bidirectional in terms of interdisciplinary collaboration. On one hand, I want to spread the machine learning technology by using it to solve outstanding problems in other disciplines. Computational biology, medical diagnosis, operations research, and robotics are just a few sample areas where uncertainty is inherent and machine learning can make a difference. On the other hand, I want to bring new tools, developed in other disciplines, into machine learning. I believe that mathematics, statistics, control theory, and physics will be some of the main such "collaborators" in the years to come. Tools, such as wavelets, experimental design, adaptive control, and chaotic dynamics, have the potential of contributing significantly to the core challenges of machine learning. Under this view, I envision my research career crossing the narrow borders of strict specialization while maintaining a scholarly expertise on a very promising field.

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