An interactive knowledge-driven multi-objective optimization framework for achieving faster convergence

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ABSTRACT

Users interested in solving real-world optimization problems often have many years of experience. Their intuition or knowledge is often overlooked in academic studies due to concerns regarding loss of generality. Such knowledge can be expressed as inter-variable relationships or functions, which can provide some initial guidance to a suitably-designed optimization algorithm. Alternatively, knowledge about variable interactions can also be extracted algorithmically during the optimization by analyzing the better solutions progressively found over iterations - a process termed innovization. Any common pattern extracted from good solutions discovered during an optimization run can be used as a repair operator to modify candidate solutions, but the key aspect is to strike a balance between the relevance of the pattern identified and the extent of its use in the repair operator, lest the learned patterns turn out to be properties of unpromising search directions or `blind alleys'.

In this dissertation, we propose a framework combining both user-supplied and algorithmically-extracted knowledge to repair solutions during an optimization run in an online fashion. Such a framework is also interactive, allowing the user to provide inputs at any point during the optimization.
We show the step-wise modifications required for an evolutionary multi-objective (EMO) framework to allow for: (a) initial user-provided knowledge, (b) automated knowledge extraction and application using innovization methods, and (c) allowing the user to interact with the framework at any point during the optimization run. The path to creating such a framework is systematically performed one step at a time, starting from creating an efficient method of representing problem knowledge, designing a suitable automated innovization procedure, and finally interleaving human-provided and machine-extracted knowledge. We show that such a framework can achieve faster convergence across a variety of practical optimization problems. Some future research directions are also discussed.