■ 연구논문 요약문

논문제목	Distribution-robust Loss-averse Optimization
게재정보	Optimization Letters, 11 (1), 2017.01
개요	- As an alternative to stochastic programming, distribution-robust (distribution-free) optimization has been suggested and applied in many areas. This approach, also known as ambiguity-averse optimization, assumes incomplete knowledge of the relevant distribution and seeks to find a solution that performs well independently of the particular distribution realized. - This paper proposes, for both ambiguity-averse and loss-averse optimization, a general modeling framework that is applicable to many practical decision-making problems. The proposed objective function is comprised of two parts: the nominal value and the downside loss. In this context, the decision maker tries to maximize the nominal value with some protection against downside loss due to uncertainty.
연구결과	- The distribution-robust loss-averse optimization problem is introduced - It is shown to be transformable into a simpler equivalent optimization problem. - The relation of the proposed model with other optimization frameworks, including robust optimization (Ben-Tal and Nemirovski) and mean-variance optimization (Markowitz), is analyzed. - The two-sided penalty case is also analyzed, and a method to handle equality constraints is proposed.
활용분야 및 기대효과	- The distribution-robust loss-averse optimization framework presented in this paper is versatile in its modeling capability. With it, we can choose not only the suitable loss aversion parameter but also the appropriate form of the loss function. - The approach can be applied to the objective function as well as to any type of linear constraints. Moreover, it is quite general in that it can be viewed as a generalization of other comparable optimization approaches under uncertainty. - Another notable property of the framework is its admitting of an intuitively clear interpretation. Hence the proposed framework and approach can be a viable tool for modeling many optimization problems under uncertainty.