Risk-sensitive Distributional Reinforcement Learning for Algorithmic Trading

Rong Guo, Egemen Okur, Arsham Afsardeir, Klaus Obermayer

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Todo list

1 Domain Background

Paper	**Summary**	**Drawbacks w.r.t ours**
RSQ (Shen et al., 2014b,a)	Utility function over TD error, convergence and optimality guarantees	Tabular Q; Trading on limit order market
Ensemble actor-critic (Yang et al., 2020)	Ensemble trained by returns but the winner is selected by Sharp ration	Add-hoc risk strategies
Exponential Bellman Equation (Fei et al.)	Theoretical guarantees; An instantiation of distributional RL through the MGF of rewards	theoretical paper, no application
Risk-senstive Distributional Q (Bodnar et al., 2020; Dabney et al., 2018a)	Various risk measures; Discrete and continuous action space Q-learning	robotics

2 Problem and Solution Statement

2.1 Portfolio Optimization as A Reinforcement Learning Problem

In many financial decision making tasks, expected returns fail to describe the real outcomes. Outcomes must be reasoned through considering not only the expected value, but also volatility and risk. The outcome (return) is a random variable.

Deep reinforcement learning has shown to be a useful too for portfolio optimization (Zhang et al., 2020). The recent distributional reinforcement learning (Bellemare et al., 2017; Dabney et al., 2018b) endows policies with risk-sensitive strategies, by taking the entire value distributions into account.

Technical novelty? not all original, but are rather an interesting use-case/application of existing methods and are a useful contribution.

3 Dataset & Input & Metric

1. Environment/Experiments.
   - portfolio allocation problem
2. Benchmark model & results, which contextualises existing methods/knowledge in the domain.
   - SOTA: How are the existing work related to our methods?
   - Experiments contrasting risk-neutral with risk-sensitive RL methods
3. Metric: objectively compare the solution model with the benchmark model.
   - Returns vs. Risk
   - Sharp ration, CVaR, etc.
   - Theoretical guarantees and insights on convergence and optimatliy

4 Theoretical Workflow

4.1 End-to-end formalization

4.2 Using Distributional RL for Risk Awareness

4.3 Convergence Analysis

5 Network Architecture

- MLP

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