“**Dynamic stochastic optimization problems with financial applications in mind**”

Diana Barro

This course deals with optimization problems under uncertainty. Such problems have many applications in, e.g., energy, healthcare, logistics, finance, and sustainability. The purpose of this part of the reading seminar is to address problems relevant to personal finance and pensions in a multi-period stochastic framework.

The seminar discusses various approaches and their possible cooperation. Specifically, the useful interactions between stochastic programming and optimal control are presented (Barro et al. 2009, Konicz et al. 2015). The goal is to design policies in decision-making under uncertainty for portfolio management problems encompassing different problem formulations (e.g., expected value optimization, probabilistic constraints, stochastic dominance relations, and risk measures). Applications to dynamic portfolio problems and risk management are discussed.

Backtesting for investment strategies in a phyton environment experiment with various investment techniques and algorithms will be presented and discussed.

1) Barro, D., Consigli, G., and Varun, V. (2022): *A stochastic programming model for dynamic portfolio management with financial derivatives*. Journal of Banking & Finance, 140, 106445.

2) Barro, D, Canestrelli, E, and Consigli, G. (2019): *Volatility versus downside risk: performance protection in dynamic portfolio strategies*. Computational Management Science, 16, 433-479.

3) Barro, D., and Canestrelli, E. (2016): *Combining stochastic programming and optimal control to decompose multistage stochastic optimization problems*. OR Spectrum, 38, 711-742.

4) Konicz, A.K., Pisinger, D., Rasmussen, K., and Steffensen, M. (2015): *A combined stochastic programming and optimal control approach to personal finance and pensions*. OR Spectrum 37, 583–616

5) Powell, W.B. (2014): *Clearing the Jungle of Stochastic Optimization*. In: INFORMS Tutorials in Operations Research, 109-137.

“**Intelligent bio-inspired methodologies for static and dynamic optimization in finance**”

Marco Corazza

Static and dynamic optimization techniques play a crucial role in the development of financial trading systems, as well as in portfolio selection and management.

With reference to the financial trading system and static portfolio selection, developing methods and tools that can effectively operate in real financial markets is no easy task. Indeed, one must assess risk through measures that, on one hand, satisfy appropriate formal properties, and on the other hand, are better suited to the non-normal return distributions characterizing the stock markets. Furthermore, one must consider the practices and rules of the portfolio management industry that can impact the portfolio selection process, such as the use of bounds for the minimum and maximum number of stocks to trade. As a result, the constrained global optimization problem that arise are potentially highly nonlinear, nondifferentiable, nonconvex, and mixed-integer, contributing to their NP-hardness. Therefore, the development of ad hoc solution approaches is usually necessary to find optimal solutions to these problems. However, as of now, efficient and effective solution algorithms for such a general scheme of mathematical programming problems do not exist. Thus, in order to offer a computationally cheap yet reliable sub-optimal good solution to these problems and to investigate their numerical complexity, we consider a couple of bio-inspired metaheuristics (see [Maringer, 2005]): Genetic Algorithms and Particle Swarm Optimization (see [Corazza et al., 2013], [Corazza et al., 2021], [Corazza et al., 2024]). The choice of bio-inspired metaheuristics as global optimizers is also motivated by the fact that ≪[t]*hey are more universal and less exacting with respect to an optimization problem*≫ (see [Feoktistov, 2006]).

With regard to dynamic investment and portfolio management, we explore automated methods based on a self-adaptive machine learning approach known as Reinforcement Learning (see [Barto and Sutton, 2018]). This learning approach involves an agent dynamically interacting with an environment. During this interaction, the agent perceives the state of the environment and takes an action. Based on such action, the environment provides a negative or positive reward. This process allows the agent to heuristically identify a policy that maximizes cumulative rewards over time. In financial applications, the agent is typically a trader or portfolio manager, and the environment is a financial market. Upon perceiving the market's state, the agent decides whether to sell or buy a given asset, and in response, the market provides a loss or gain. This enables the online detection of a trading strategy for the continual maximization of cumulative performance measures over time. Note that RL methodologies do not provide optimal solutions but rather good near-optimal ones. Now, let's address the question: why not resort to more classical stochastic dynamic programming methods that guarantee the achievement of optimal solutions? Generally speaking, the latter type of methods requires a precise description of the probabilistic features of the investigated financial markets. However, the dynamics of financial markets are often unknown and structurally time-varying, making it impossible to provide such a required precise description. In contrast, RL does not need a priori knowledge of the transition probability matrices. Applications to dynamic trading and dynamic portfolio management are considered (see, e.g. [Bertoluzzo and Corazza 2012], [Deng et al. 2017], [Corazza et al. 2019], [Corazza 2020], [Corazza et al. 2021], [Garcia and Marinenko (2024)]).

For both considered topics, namely metaheuristics and RL methods applied to finance, we also contemplate their software implementations within the Matlab® environment.

1) Barto, A.G., and Sutton, R.S. (2018): *Reinforcement Learning: An Introduction, Second Edition.* The MIT Press.

2) Bertoluzzo, F., and Corazza M. (2012): *Testing different Reinforcement Learning configurations for financial trading: Introduction and applications.* Procedia Economics and Finance, 3:68-77.

3) Corazza, M. (2020): *Q-Learning-based financial trading: Some results and comparisons.* In: Progresses in Artificial Intelligence and Neural Systems, Springer, 184:343-355.

4) Corazza, M., di Tollo, G., Fasano, G., and Pesenti, R. (2021): *A novel hybrid PSO-based metaheuristic for costly portfolio selection problems.* Annals of Operations Research, 304:109-137.

5) Corazza, M, Fasano, G, and Gusso, R. (2013): *Particle Swarm Optimization with non-smooth penalty reformulation, for a complex portfolio selection problem.* Applied Mathematics and Computation, 224:611–624.

6) Corazza, M., Fasano, G., Gusso, R., and Pesenti, R. (2019): *A comparison among Reinforcement Learning algorithms in financial trading systems.* Working Papers, Department of Economics, Ca' Foscari University of Venice, 33/WP/2019

7) Corazza, M., Pizzi, C., and Marchioni A. (2024): *A financial trading system with optimized indicator setting, trading rule definition, and signal aggregation through Particle Swarm Optimization.* Computational Management Science. [In press.]

8) Deng Y, Bao F, Kong Y, Ren Z, Dai Q (2017): *Deep Direct Reinforcement Learning for financial signal representation and trading.* IEEE Transactions on Neural Networks and Learning Systems, 28: 653-664.

9) Garcia, R., and Marinenko A. (2024): *Portfolio Allocation and Reinforcement Learning.* In: Artificial Intelligence and Beyond for Finance, World Scientific Publishing. [In press.]

10) Maringer, D. (2005): *Portfolio Management with Heuristic Optimization.* Springer.

11) Feoktistov, V. (2006): *Differential Evolution. In Search of Solutions.* Springer.