Chapter XV

Financial Trading Systems: Is Recurrent Reinforcement Learning the Way?

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ABSTRACT

In this chapter we propose a financial trading system whose trading strategy is developed by means of an artificial neural network approach based on a learning algorithm of the recurrent reinforcement type. In general terms, this kind of approach consists, first, of directly specifying a trading policy based on some predetermined investor’s measure of profitability, and second, of directly setting the financial trading system while using it. In particular, with respect to the prominent literature, in this contribution we take into account as a measure of profitability the reciprocal of the returns weighted direction symmetry index instead of the widespread Sharpe ratio, and we obtain the differential version of the measure of profitability we consider and all the related learning relationships. Finally, we propose a simple procedure for the management of drawdown-like phenomena, and finally, we apply our financial trading approach to some of the most prominent assets of the Italian stock market.

INTRODUCTION

When an economic agent invests capital in financial markets, she or he has to make decisions under uncertainty. In such a context, the task consists of suitably dealing with financial risk in order to maximize some predetermined measure of profitability. A widespread class of tools that
Financial Trading Systems

is used to support such risky decisions is the one of the financial trading system (FTS).

A standard approach that is usually followed to specify an FTS involves the following.

• Identifying one or more variables (asset prices, transaction volumes, etc.) related to the time behavior of one or more suitable quantities of interest (e.g., trading signals).
• Utilizing the current and past values of these variables to forecast (or, more in general, to extract information concerning them) the future values of the suitable quantities of interest.
• Using these predictions and information to implement a trading strategy by which to make effective trades.

The distinctly operative valence of FTSs has obviously made them popular for a long time among professional investors and practitioners. A lot of books have been devoted to the working utilization of these tools (see, among the various ones, Appel, 1979; Murphy, 1999; Nison, 1991; Wilder, 1978).

Nevertheless, although only in recent years, the academic world has also begun to (partially) recognize the soundness of some of the features related to FTSs (see, among the first ones, Lee & Swaminathan, 2000; Lo, Mamaysky, & Wang, 2000). Moreover, the really enormous, and continuously increasing, mass of collected financial data has led to the development of FTSs whose information extraction processes are based on data mining methodologies (see, for example, Corazza, Vanni, & Loschi, 2002; Plihon, Wu, & Gardarin, 2001).

Alternative approaches to the standard building of FTSs have been proposed both in the operative literature and in the academic ones. Among the approaches belonging to the latest category, in this chapter we consider the ones that exploit artificial neural network (ANN) methodologies based on learning of the recurrent reinforcement type. In general terms, these approaches including the following.

• Directly specifying a trading policy based on some predetermined investor’s measure of profitability (in such a manner one avoids to have to identify the quantities of interest, and avoids to have to perform the predictions and information extraction concerning such quantities).
• Directly setting the frame and the parameters of the FTS while using it (in such a way one can avoid to carry out the off-line setting of the trading system).

Among the first contributions in this research field, we recall Moody, Wu, Liao, and Saffell (1998), Moody and Saffell (2001), and Gold (2003). In general, they show that such strategies perform better than the ones based on supervised learning methodologies when market frictions are considered. In Moody et al., the authors develop and utilize a recurrent reinforcement learning (RRL) algorithm in order to set an FTS that, taking into account transaction costs, maximizes an appropriate investor’s utility function based both on the well-known Sharpe ratio and on its differential version. Then, they show by controlled experiments that the proposed FTS performs better than standard FTSs. Finally, the authors use their FTS to make profitable trades with respect to assets of the U.S. financial markets. In Moody and Saffell, the authors mainly compare FTSs developed by using RRL methodologies with FTSs developed by using stochastic dynamic programming methodologies. In general, they show by extensive experiments that the former approach is better than the latter one. In Gold, the author considers an FTS similar to the one developed in Moody et al. and applies it to financial high-frequency data, obtaining profitable performances.