FINANCIAL SIGNAL PROCESSING AND MACHINE LEARNING

EDITED BY
ALI N. AKANSU
SANJEEV R. KULKARNI
DMITRY M. MALIOUTOV

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Ali N. Akansu

New Jersey Institute of Technology, USA

Sanjeev R. Kulkarni

Princeton University, USA

Dmitry Malioutov

IBM T.J. Watson Research Center, USA

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List of Contributors

Ali N. Akansu, New Jersey Institute of Technology, USA

Marco Cuturi, Kyoto University, Japan

Alexandre d'Aspremont, CNRS - Ecole Normale supérieure, France

Christine De Mol, Université Libre de Bruxelles, Belgium

Jianqing Fan, Princeton University, USA

Jun-ya Gotoh, Chuo University, Japan

Nicholas A. James, Cornell University, USA

Prabhanjan Kambadur, Bloomberg L.P., USA

Alexander Kreinin, Risk Analytics, IBM, Canada

Sanjeev R. Kulkarni, Princeton University, USA

Yuan Liao, University of Maryland, USA

Han Liu, Princeton University, USA

Matthew Lorig, University of Washington, USA

Aurélie C. Lozano, IBM T.J. Watson Research Center, USA

Ronny Luss, IBM T.J. Watson Research Center, USA

Dmitry Malioutov, IBM T.J. Watson Research Center, USA

David S. Matteson, Cornell University, USA

William B. Nicholson, Cornell University, USA

Ronnie Sircar, Princeton University, USA

Akiko Takeda, The University of Tokyo, Japan

Mustafa U. Torun, New Jersey Institute of Technology, USA

Stan Uryasev, University of Florida, USA

Onur Yilmaz, New Jersey Institute of Technology, USA

Preface

This edited volume collects and unifies a number of recent advances in the signal-processing and machine-learning literature with significant applications in financial risk and portfolio management. The topics in the volume include characterizing statistical dependence and correlation in high dimensions, constructing effective and robust risk measures, and using these notions of risk in portfolio optimization and rebalancing through the lens of convex optimization. It also presents signal-processing approaches to model return, momentum, and mean reversion, including both theoretical and implementation aspects. Modern finance has become global and highly interconnected. Hence, these topics are of great importance in portfolio management and trading, where the financial industry is forced to deal with large and diverse portfolios in a variety of asset classes. The investment universe now includes tens of thousands of international equities and corporate bonds, and a wide variety of other interest rate and derivative products-often with limited, sparse, and noisy market data.

Using traditional risk measures and return forecasting (such as historical sample covariance and sample means in Markowitz theory) in high-dimensional settings is fraught with peril for portfolio optimization, as widely recognized by practitioners. Tools from high-dimensional statistics, such as factor models, eigen-analysis, and various forms of regularization that are widely used in real-time risk measurement of massive portfolios and for designing a variety of trading strategies including statistical arbitrage, are highlighted in the book. The dramatic improvements in computational power and special-purpose hardware such as field programmable gate arrays (FPGAs) and graphics processing units (GPUs) along with low-latency data communications facilitate the realization of these sophisticated financial algorithms that not long ago were "hard to implement."

The book covers a number of topics that have been popular recently in machine learning and signal processing to solve problems with large portfolios. In particular, the connections between the portfolio theory and sparse learning and compressed sensing, robust optimization, non-Gaussian data-driven risk measures, graphical models, causal analysis through temporal-causal modeling, and large-scale copula-based approaches are highlighted in the book.

Although some of these techniques already have been used in finance and reported in journals and conferences of different disciplines, this book attempts to give a unified treatment from a common mathematical perspective of high-dimensional statistics and convex optimization. Traditionally, the academic quantitative finance community did not have much overlap with the signal and information-processing communities. However, the fields are seeing more interaction, and this trend is accelerating due to the paradigm in the financial sector which has embraced state-of-the-art, high-performance computing and signal-processing technologies. Thus, engineers play an important role in this financial ecosystem. The goal of this edited volume is to help to bridge the divide, and to highlight machine learning and signal processing as disciplines that may help drive innovations in quantitative finance and electronic trading, including high-frequency trading.

The reader is assumed to have graduate-level knowledge in linear algebra, probability, and statistics, and an appreciation for the key concepts in optimization. Each chapter provides a list of references for readers who would like to pursue the topic in more depth. The book, complemented with a primer in financial engineering, may serve as the main textbook for a graduate course in financial signal processing.

We would like to thank all the authors who contributed to this volume as well as all of the anonymous reviewers who provided valuable feedback on the chapters in this book. We also gratefully acknowledge the editors and staff at Wiley for their efforts in bringing this project to fruition.

Contents

1

Overview

Financial Signal Processing and Machine Learning

Ali N. Akansu[1], Sanjeev R. Kulkarni[2], and Dmitry Malioutov[3]
[1]*New Jersey Institute of Technology, USA*
[2]*Princeton University, USA*
[3]*IBM T.J. Watson Research Center, USA*

1.1 Introduction

In the last decade, we have seen dramatic growth in applications for signal-processing and machine-learning techniques in many enterprise and industrial settings. Advertising, real estate, healthcare, e-commerce, and many other industries have been radically transformed by new processes and practices relying on collecting and analyzing data about operations, customers, competitors, new opportunities, and other aspects of business. The financial industry has been one of the early adopters, with a long history of applying sophisticated methods and models to analyze relevant data and make intelligent decisions – ranging from the quadratic programming formulation in Markowitz portfolio selection (Markowitz, 1952), factor analysis for equity modeling (Fama and French, 1993), stochastic differential equations for option pricing (Black and Scholes, 1973), stochastic volatility models in risk management (Engle, 1982; Hull and White, 1987), reinforcement learning for optimal trade execution (Bertsimas and Lo, 1998), and many other examples. While there is a great deal of overlap among techniques in machine learning, signal processing and financial econometrics, historically, there has been rather limited awareness and slow permeation of new ideas among these areas of research. For example, the ideas of stochastic volatility and copula modeling, which are quite central in financial econometrics, are less known in the signal-processing literature, and the concepts of sparse modeling and optimization that have had a transformative impact on signal processing and statistics have only started to propagate slowly into financial

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applications. The aim of this book is to raise awareness of possible synergies and interactions among these disciplines, present some recent developments in signal processing and machine learning with applications in finance, and also facilitate interested experts in signal processing to learn more about applications and tools that have been developed and widely used by the financial community.

We start this chapter with a brief summary of basic concepts in finance and risk management that appear throughout the rest of the book. We present the underlying technical themes, including sparse learning, convex optimization, and non-Gaussian modeling, followed by brief overviews of the chapters in the book. Finally, we mention a number of highly relevant topics that have not been included in the volume due to lack of space.

1.2 A Bird's-Eye View of Finance

The financial ecosystem and markets have been transformed with the advent of new technologies where almost any financial product can be traded in the globally interconnected cyberspace of financial exchanges by anyone, anywhere, and anytime. This systemic change has placed real-time data acquisition and handling, low-latency communications technologies and services, and high-performance processing and automated decision making at the core of such complex systems. The industry has already coined the term *big data finance*, and it is interesting to see that technology is leading the financial industry as it has been in other sectors like e-commerce, internet multimedia, and wireless communications. In contrast, the knowledge base and exposure of the engineering community to the financial sector and its relevant activity have been quite limited. Recently, there have been an increasing number of publications by the engineering community in the finance literature, including *A Primer for Financial Engineering* (Akansu and Torun, 2015) and research contributions like Akansu *et al.*, (2012) and Pollak *et al.*, (2011). This volume facilitates that trend, and it is composed of chapter contributions on selected topics written by prominent researchers in quantitative finance and financial engineering.

We start by sketching a very broad-stroke view of the field of finance, its objectives, and its participants to put the chapters into context for readers with engineering expertise. Finance broadly deals with all aspects of money management, including borrowing and lending, transfer of money across continents, investment and price discovery, and asset and liability management by governments, corporations, and individuals. We focus specifically on trading where the main participants may be roughly classified into hedgers, investors, speculators, and market makers (and other intermediaries). Despite their different goals, all participants try to balance the two basic objectives in trading: to maximize future expected rewards (returns) and to minimize the risk of potential losses.

Naturally, one desires to buy a product cheap and sell it at a higher price in order to achieve the ultimate goal of profiting from this trading activity. Therefore, the expected return of an investment over any holding time (horizon) is one of the two fundamental performance metrics of a trade. The complementary metric is its variation, often measured as the standard deviation over a time window, and called investment risk or market risk.[1] Return and risk are two typically conflicting but interwoven measures, and risk-normalized return (Sharpe ratio)

[1] There are other types of risk, including credit risk, liquidity risk, model risk, and systemic risk, that may also need to be considered by market participants.

finds its common use in many areas of finance. Portfolio optimization involves balancing risk and reward to achieve investment objectives by optimally combining multiple financial instruments into a portfolio. The critical ingredient in forming portfolios is to characterize the statistical dependence between prices of various financial instruments in the portfolio. The celebrated Markowitz portfolio formulation (Markowitz, 1952) was the first principled mathematical framework to balance risk and reward based on the covariance matrix (also known as the variance-covariance or VCV matrix in finance) of returns (or log-returns) of financial instruments as a measure of statistical dependence. Portfolio management is a rich and active field, and many other formulations have been proposed, including risk parity portfolios (Roncalli, 2013), Black–Litterman portfolios (Black and Litterman, 1992), log-optimal portfolios (Cover and Ordentlich, 1996), and conditional value at risk (cVaR) and coherent risk measures for portfolios (Rockafellar and Uryasev, 2000) that address various aspects ranging from the difficulty of estimating the risk and return for large portfolios to the non-Gaussian nature of financial time series, and to more complex utility functions of investors.

The recognition of a price inefficiency is one of the crucial pieces of information to trade that product. If the price is deemed to be low based on some analysis (e.g. fundamental or statistical), an investor would like to buy it with the expectation that the price will go up in time. Similarly, one would shortsell it (borrow the product from a lender with some fee and sell it at the current market price) when its price is forecast to be higher than what it should be. Then, the investor would later buy to cover it (buy from the market and return the borrowed product back to the lender) when the price goes down. This set of transactions is the building block of any sophisticated financial trading activity. The main challenge is to identify price inefficiencies, also called *alpha* of a product, and swiftly act upon it for the purpose of making a profit from the trade. The efficient market hypothesis (EMH) stipulates that the market instantaneously aggregates and reflects all of the relevant information to price various securities; hence, it is impossible to beat the market. However, violations of the EMH assumptions abound: unequal availability of information, access to high-speed infrastructure, and various frictions and regulations in the market have fostered a vast and thriving trading industry.

Fundamental investors find alpha (i.e., predict the expected return) based on their knowledge of enterprise strategy, competitive advantage, aptitude of its leadership, economic and political developments, and future outlook. Traders often find inefficiencies that arise due to the complexity of market operations. Inefficiencies come from various sources such as market regulations, complexity of exchange operations, varying latency, private sources of information, and complex statistical considerations. An *arbitrage* is a typically short-lived market anomaly where the same financial instrument can be bought at one venue (exchange) for a lower price than it can be simultaneously sold at another venue. Relative value strategies recognize that similar instruments can exhibit significant (unjustified) price differences. Statistical trading strategies, including statistical arbitrage, find patterns and correlations in historical trading data using machine-learning methods and tools like factor models, and attempt to exploit them hoping that these relations will persist in the future. Some market inefficiencies arise due to unequal access to information, or the speed of dissemination of this information. The various sources of market inefficiencies give rise to trading strategies at different frequencies, from high-frequency traders who hold their positions on the order of milliseconds, to midfrequency trading that ranges from intraday (holding no overnight position) to a span of a few days, and to long-term trading ranging from a few weeks to years. High-frequency trading requires state-of-the-art computing, network communications, and