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Efficient Simulation of Financial Stress Testing Scenarios with Suppes-Bayes Causal Networks

Gelin Gao[a], Bud Mishra[a], Daniele Ramazzotti[b]

[a]New York University, New York, USA
[b]Stanford University, Stanford, California, USA

Abstract

The most recent financial upheavals have cast doubt on the adequacy of some of the conventional quantitative risk management strategies, such as VaR (Value at Risk), in many common situations. Consequently, there has been an increasing need for verisimilar financial stress testings, namely simulating and analyzing financial portfolios in extreme, albeit rare scenarios. Unlike conventional risk management which exploits statistical correlations among financial instruments, here we focus our analysis on the notion of probabilistic causation, which is embodied by Suppes-Bayes Causal Networks (SBCNs), SBCNs are probabilistic graphical models that have many attractive features in terms of more accurate causal analysis for generating financial stress scenarios.

In this paper, we present a novel approach for conducting stress testing of financial portfolios based on SBCNs in combination with classical machine learning classification tools. The resulting method is shown to be capable of correctly discovering the causal relationships among financial factors that affect the portfolios and thus, simulating stress testing scenarios with a higher accuracy and lower computational complexity than conventional Monte Carlo Simulations.

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Stress Testing, Graphical Models, Causality, Suppes-Bayes Causal Networks, Classification, Decision Trees

1. Introduction

Risk management has increasingly become a central part of world finance in the past century. Quantitative risk management generally targets the risk of insolvency: namely, the depletion of capital of a trading agency to the point that the trading agency has to stop its operations. For any trading agency, its account consists of cash, stocks, bonds or other financial instruments, and net equity, where *Equity* = *Cash* + *Financial Instruments*. The task of quantitative risk management is to calculate the amount of equity that has to be reserved so that the net equity will not drop to negative [1]. Depending on different financial agencies, hedge funds, banks or clearing houses, and on different financial instruments, stocks, bonds, or derivatives, the method of risk management may vary, but the central idea behind conventional risk management remains: we assess the statistical distribution of the asset (or portfolio), and estimate the worst-case scenarios, generally by methods such as Monte Carlo Simulation [2].

However, such conventional approach got discredited by the recent events leading to major financial catastrophes. For example, in the recent 2008 financial crisis, the reserves calculated the risk by using methods such as VaR (Value at Risk) [3] which proved to be painfully inadequate. Because of that, a different method had to be introduced, namely the one of *stress testing*. Stress testing refers to the analysis or simulation of the response of financial instruments or

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institutions, given intensely stressed scenarios that may lead to a financial crisis [4]. For example, narrowly speaking, stress testing may model the response of a portfolio when Dow Jones suddenly drops by 5%. The difference between stress testing and conventional risk management is that stress testing deliberately introduces an adversarial, albeit plausible event, which may be highly improbable but not implausible – e.g., a black swan event triggering an unforeseen scenario. Thus, stress testing must be capable of observing the response of financial instruments or institutions under extremely rare scenarios. Such scenarios may be deemed to be unlikely to be observed in conventional risk management, where the simpler system may fail to estimate a 99$^{\text{th}}$ percentile of the loss distribution, and subsequently leading to a claim that, with 99% confidence level, a specific portfolio will perform well, giving a false sense of security.

Recently, many different approaches have been developed to implement some form of stress testing. In terms of stress scenario generation, the most direct method is the historical one, in which observed events from the past are used to test contemporary portfolios [5]. The historical approach is objective since it is based on actual events, but it is not necessarily relevant under the present conditions, which necessitate some hypothetical methods. As an alternative, the event-based method has been proposed in order to quantify a specific hypothetical stress scenario subjectively, by domain experts, and then estimate the possible consequence of such event using macroeconomic and financial models [5]. Event-based methods rely intensively on expert judgement on whether a hypothetical event will be severely-damaging, albeit still plausible to occur. Sometime such judgement becomes difficult when the relationship between the underlying risk factors and the portfolio is unknown. To ensure a scenario is damaging to the portfolio, a portfolio-based method has been also studied in order to link scenarios directly with the portfolio [5]. To this extent, portfolio-based methods rely on Monte Carlo Simulation to identify the movements of risk factors that stress the given portfolio most severely, however brute force Monte Carlo Simulation is computationally inefficient especially when dealing with many risk factors. To solve this problem, Rebonato et al. proposed a sampling approach based on Bayesian networks in [6].

Roadmap: This paper is organized as follow. Next section describes the theoretical foundations of our approach and, in particular, it shows how combining the expressivity of Suppes-Bayes Causal Networks together with classical classification approaches can effectively capture the dynamics of financial stress testing. Section 3 provides an algorithm for the efficient inference of SBCNs from financial data, discusses its performance in-depth and shows on realistic simulated data how our approach is preferable in comparison to the standard Bayesian methods. Section 4 concludes the paper.

2. Method

In this work we use Bayesian Graphical Models [7], popularly known as Bayesian networks, as a framework to assess stress testing, as previously done in this context by [6]. Bayesian networks have long been used in biological modeling such as -omics data analysis, cancer progression or genetics [8, 9, 10], but their application to financial data analysis has been rare. Roughly speaking, Bayesian networks attempt to exploit the conditional independence among random variables, whether the variables represent genes or financial instruments. In this paper we adopt a variation of the traditional Bayesian networks as done in [11, 12], where the authors show how constraining the search space of valid solutions by means of a causal theory grounded in Suppes' notion of probabilistic causation [13] can be exploited in order to devise better learning algorithms. Also, by accounting for Suppes' notion of probabilistic causation, we ensure not only conditional independence but also *prima facie* causal relations among variables, leading us to a better definition of the actual factors leading to risk. Moreover, through a maximum likelihood optimization scheme which makes use of a regularization score, we also attempt to only retain edges in the Bayesian network (graphically depicted as a directed acyclic graph, DAG) that correspond to only genuine causation, while eliminating all the spurious causes [11, 12].

Yet, given the inferred network, we can sample from it to generate plausible scenarios, though not necessarily adversarial or rare. In the case of stress testing, it is crucial to also account for rare configurations, for this reason, we adopt auxiliary tools from machine learning to discover random configurations that are both unexpected and undesired.

In this Section we expand the concept sketched above and specifically we provide a background of our framework, by describing the adopted Bayesian models and causal theories and we show how classification given an inferred SBCN can effectively guide stress testing simulations.