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Asset Allocation Method Based on Sentiment Signals and Causal Information using Multi-asset Classes

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Abstract

In this study, we demonstrate the usefulness of financial text for asset allocation with multi-asset classes, including stocks and bonds, by creating polarity indexes for several types of financial news through natural language processing. We performed clustering using a change-point detection algorithm on the created polarity indexes. We also constructed a multi-asset portfolio using an optimization algorithm and rebalanced it based on the detected change points. The results show that the proposed asset allocation method performed better than the comparison method, suggesting that polarity indexes can be useful in constructing asset allocation methods with multi-asset classes.

Keywords: Financial news, MLM scoring, causal inference, change-point detection, risk-parity portfolio

1 Introduction

1.1 Background

In this study, we propose that financial texts can be useful for tactical asset allocation methods using a multi-asset class. This can be accomplished using natural language processing and statistical causal inference to create rebalancing signals. Numerous studies have been conducted on investment techniques using machine learning. In particular, there is a growing body of research on asset allocation, including the derivation of investment signals and calculation of investment ratios [1,2]. In this study, we focus on the point at which portfolio prices change rapidly due to external factors, that is, the point of regime change. Regimes in finance theory are the invisible market states, such as expansion, recession, bulls, and bears. Some studies attempted to capture market alpha by incorporating these regime changes into investment strategies [3,4]. We will delve one step further and focus on measuring future regime changes. In this study, we specifically draw on the studies presented in [5]. If the information on future regime changes (i.e., future changes in the market environment) is known, active management with a higher degree of freedom becomes possible. However, because there are certain limitations in calculating future regimes using only traditional

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