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A Top-Down Changepoint Detection Framework Based on Two-State Markov-Switching Model

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Abstract

We propose a robust framework for multiple changepoint detection (CPD) in time series with mean shifts. The key idea is to move CPD from the raw data space to the probability space, leveraging a two-state Markov-switching (2S-MS) model. We first fit a 2S-MS model in mean to the series, compute the smoothed posterior state probabilities, and then run a modern segmentation method on these bounded probabilities. We implement a top-down recursion that refits the 2S-MS model within detected segments until no further changepoints are found. Simulations and an empirical study on the VIX index show that the approach outperforms standard methods on financial data. Although we focus on mean shifts in this paper, the framework is extensible to volatility shifts and joint mean–variance shifts.

Keywords: Changepoint detection, Markov-switching, Posterior probability, PELT, Binary segmentation

1 Problem and Motivation

Classical CPD algorithms such as Binary Segmentation (BinSeg), Wild Binary Segmentation (WBS), and Pruned Exact Linear Time (PELT) are powerful in the existing literature [3, 5, 4]. Financial series, however, are noisy, heavy-tailed, and often contain outliers. These features may reduce the robustness of direct CPD on the raw series. Our goal is proposing a method that preserves the efficiency of modern CPD while improving its effectiveness and robustness for financial data.

2 Method

Let $\{y_t\}_{t=1}^{T}$ be a univariate time series. We fit a 2S-MS in-mean model:

$$y_t = \mu_{s_t} + \varepsilon_t, \quad s_t \in \{0,1\}, \quad \Pr(s_t = j \mid s_{t-1} = i) = p_{ij},$$

with $\varepsilon_t \sim \mathcal{N}(0, \sigma^2)$. Using standard filtering, we obtain the smoothed posterior probabilities $\pi_t = \Pr(s_t = 1 \mid y_{1:T})$ [1, 2]. The bounded $\pi_t \in [0,1]$ clusters near 0 or 1 when a true mean shift exists, and wanders otherwise.

A classic CPD method, such as PELT, can be applied to $\{\pi_t\}$ using a piecewise-constant cost and an information criterion penalty [4]. Detected changepoints define segments. Within each segment we refit the MS model and repeat the CPD step on the fitted probability, until no further changepoints are identified. The entire procedure is conducted in the following two-down fashion.

3 Algorithm

1. Fit a 2S-MS model to $\{y_t\}$ and compute $\{\pi_t\}$.
2. Apply a CPD method to $\{\pi_t\}$ to obtain changepoints.

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3. Refit the MS model within each segment and repeat step 2.
4. Stop when no new changepoints are found.

The bounded posterior probability series π_t compresses extremes and limits the influence of outliers, acting as a variance-stabilizing transformation that yields clearer plateau-like signals for segmentation [4, 5].

4 Simulation Studies

We design two experiments to demonstrate the effectiveness of our framework.

Part A: Simulated posterior probability series with mean shifts, varying number of changepoints, sample size, and outliers. We compare PELT, BinSeg, and WBS to select the best segmentation algorithm, which will be used for the subsequent analysis.

Part B: Simulated time series with mean shifts, varying number of changepoints, sample size, and outliers. We compare our 2S-MS method with detection using PELT, BinSeg, and WBS.

Metrics. F1 score, false positives/negatives, mean absolute error of locations, and structural distance statistics [6].

Findings: In Part A, PELT is the best-performing method on probability series. In Part B, our top-down 2S-MS–PELT pipeline dominates classic CPD algorithms, especially under the scenarios with outliers. It consistently yields the highest F1 and the most accurate localization.

5 Empirical Application

We apply all methods to daily VIX. Detected changepoints produced by the 2S-MS-PELT align the best with well-known empirical market stress episodes. Relative to direct PELT, BinSeg, and WBS, our method yields more stable and interpretable regimes. This supports the framework for economic and financial monitoring.

6 Conclusion

The proposed top-down 2S-MS CPD approach is simple to implement, fast, and accurate for empirical applications. The framework is modular: one can target volatility shifts with an MS-in-variance model or detect joint mean–variance shifts by combining such features within the 2S-MS model.

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