

A Computational Inference Framework for Augmented Zero-Inflated Compound Poisson -Gamma Processes with Latent Jump Recovery

Shih-Feng Huang

Professor and Director, Graduate Institute of Statistics, National Central University

Abstract

This paper develops a computational inference framework for contaminated zero-inflated compound Poisson-Gamma processes. The proposed model provides a flexible representation for nonnegative time series with excess zeros, random jump magnitudes, and additive measurement noise. Direct maximum likelihood estimation is computationally challenging because the likelihood involves infinite-series representations, convolution terms, and latent jump components. To address these challenges, we construct a censoring likelihood and develop a penalized criterion for selecting the censoring threshold. Given the estimated parameters, a particle filter is employed to recover the latent jump process, and the estimated jumps are incorporated into a two-stage prediction model. The existence and uniqueness of the selected threshold are established under mild conditions. Simulation studies and empirical applications demonstrate the numerical stability and predictive performance of the proposed framework.