The Journal of Open Source Software

stochvolTMB: An R-package for likelihood estimation of stochastic volatility models

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DOI: XX.XXXXX/joss.XXXXX

Software

- Review
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Submitted:
Published:

Summary

Stochastic volatility (SV) models are often used to model financial returns that exhibit time-varying and autocorrelated variance. The first SV model was introduced by Taylor (1982) and models the logarithm of the variance as a latent autoregressive process of order one. Parameter estimation of stochastic volatility models can be challenging and a variety of methods have been proposed, such as simulated likelihood (Liesenfeld and Richard 2006), quasi-maximum likelihood (Harvey, Ruiz, and Shephard 1994) and Markov Chain Monte Carlo methods (MCMC) (Pitt and Shephard 1999; Kastner 2016). `stochvolTMB` estimates the parameters using maximum likelihood, similar to Skaug and Yu (2014). The latent variables are integrated out using the Laplace approximation. The models are implemented in `C++` using the `R`-package (R Core Team 2019) `TMB` (Kristensen et al. 2016) for fast and efficient estimation. `TMB` utilizes the `Eigen` library (Guennebaud, Jacob, and others 2010) for numerical linear algebra and `CppAD` (Bell 2005) for automatic differentiation of the negative log-likelihood. This can lead to substantial speed-up compared to MCMC methods.

Statement of need

The `stochvolTMB` `R`-package makes it easy for the user to do inference, plotting and forecasting of volatility. The `R`-package `stochvol` (Kastner 2016) also performs inference for stochastic volatility models. but differs from `stochvolTMB` as it performs Bayesian inference using MCMC and not maximum likelihood. By using optimization instead of simulation one can obtain substantial speed up, depending on the data, model, number of observations and number of MCMC samples.

Implementation

`stochvolTMB` implements stochastic volatility models of the form

$$
\begin{aligned}
y_t &= \sigma_y e^{h_t/2}\epsilon_t, \quad t = 1, \dots, T, \\
h_{t+1} &= \phi h_t + \sigma_h \eta_t, \quad t = 1, \dots, T-1, \\
\eta_t &\overset{\text{iid}}{\sim} \mathcal{N}(0,1), \\
\epsilon_t &\overset{\text{iid}}{\sim} F, \\
h_1 &\sim \mathcal{N}\left(0, \frac{\sigma_h}{\sqrt{(1-\phi^2)}}\right)
\end{aligned}
\tag{1}
$$

where y_t is the observed log return for day t, h_t is the logarithm of the conditional variance of day t, $\boldsymbol{\theta} = (\phi, \sigma_y, \sigma_h)$ is a vector of the fixed parameters and F denotes the distribution of ϵ_t. Four distributions are implemented for ϵ_t: (1) The standard normal distribution; (2) The t-distribution with ν degrees of freedom; (3) The skew-normal distribution with skewness parameter α; and (4) The leverage model where (ϵ_t, η_t) are both standard normal with correlation parameter coefficient ρ. The last three distributions add an additional fixed parameter to $\boldsymbol{\theta}$. `stochvolTMB` also supports generic functions such as `plot`, `summary`, `predict` and `AIC`. The plotting is implemented using `ggplot2` (Wickham (2016)) and data processing utilizes the `R`-package `data.table` (Dowle and Srinivasan 2019).

The parameter estimation is done in an iterative two-step procedure: (1) Optimize the joint negative log-likelihood with respect to the latent log-volatility $\boldsymbol{h} = (h_1, \ldots, h_T)$ holding $\boldsymbol{\theta}$ fixed, and (2) Optimizing the Laplace approximation of the joint negative log-likelihood w.r.t $\boldsymbol{\theta}$. This procedure is iterated until convergence. Standard deviations for the log-volatility and the fixed parameters are obtained by the delta-method (Kristensen et al. 2016).

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