Developing a Bayesian method for locating breakpoints in time series data.

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Abstract: An abstract of up to 200 words should precede the text together with 5 or 6 keywords in alphabetical order to describe the content of the paper. Authors should take great care in preparing the abstract and not simply lift it from the main text. The abstract should describe the background and contribution of the manuscript and give a clear verbal description of the results and examples, and avoid citations whenever possible. Any acknowledgements will be printed at the end of the text.

Key words: AR; Bayesian; Breakpoints; Time Series;

1 Introduction

2 Method

The Metropolis Hastings algorithm is a mechanism consisting of a Markov Chain Monte Carlo (MCMC) that samples a distribution. Our MCMC is an adaptation of BARS that have three different overarching step type, death, birth, and move. This process repeatable proposes breakpoint sets which a ratio then determines to accept or not.

2.1 Step Type

The first type of step is we will discuses is death. This death step takes one existing break point and then deletes it. The second type of step is Birth. This birth step propose a breakpoint in a random location. There are a couple of constraints on locations of acceptable proposals. A proposed breakpoint can not be an endpoint, an already existing breakpoint, or any data point that is 2 points away from an existing breakpoint. These constraints are necessary in being able to fit an auto-regressive (AR) model. The last type of step is move. Our move step is comprised of two type of moves, jump and jiggle. Jump has a 25 % chance of occurring and it is basically a death step and then an birth step. Jiggle has 75% of occurring and it moves an existing breakpoint in a small defined interval specified by the user.

2.2 Probabilities on Steps

The probabilities of choosing one step over another is specified by the user. However, the probability of doing a death and birth step is always equal to each other. When a type of step is selected based of user input, then the Metropolis Hastings ratio determinate if the proposed breakpoint set is accepted.

2.2.1 BIC

The general Metropolis Hastings ratio is the product of the Bayes factor, determined by the ratio of the posteriors, g, and the ratio of the Markov Chain Monte Carlo (MCMC) proposal densities, q, whose values depend on the current MCMC step.

$$ratio = \frac{g(\tau_n K_n | x_1, \ldots, x_t)}{g(\tau_o K_o | x_1, \ldots, x_t)} \times \frac{q(\tau_o K_o | \tau_n K_n)}{q(\tau_n K_n | \tau_o K_o)}$$

To be able to adequately analysis these ratios we need to put the ratio on a logarithmic scale.

$$\begin{aligned} log(ratio) = & \Big[log\big[g(\tau_n K_n | x_1, \ldots, x_t)\big] - log\big[g(\tau_o K_o | x_1, \ldots, x_t)\big]\Big] \\ & + \Big[log\big[q(\tau_o K_o | \tau_n K_n)\big] - log\big[q(\tau_n K_n | \tau_o K_o)\big]\Big] \end{aligned}$$

As shown by Kass and Wasserman (1995), the log of the Bayes Factor can be approximated with BIC with an error on the order of $O(n^{-1/2})$ when the data size is greater than 25 and the prior follows a normal distribution. Therefore,

$$log\big[g(\tau_n K_n | x_1, \ldots, x_t)\big] - log\big[g(\tau_o K_o | x_1, \ldots, x_t)\big] \approx \frac{-\Delta BIC}{2}$$

which means that

$$log(ratio) \approx \frac{-\Delta BIC}{2} + \Big[log\big[q(\tau_o K_o | \tau_n K_n)\big] - log\big[q(\tau_n K_n | \tau_o K_o)\big]\Big]$$

In the case of birth,

$$q(\tau_o K_o|\tau_n K_n) = c \cdot d \cdot Poisson(K_{old}, \lambda), \quad q(\tau_n K_n|\tau_o K_o) = c \cdot b \cdot Poisson(K_{old}, \lambda).$$

When the chosen MCMC step is death,

$$q(\tau_o K_o|\tau_n K_n) = c \cdot b \cdot Poisson(K_{new}, \lambda), \quad q(\tau_n K_n|\tau_o K_o) = c \cdot d \cdot Poisson(K_{old}, \lambda).$$

Given the equations above we have that c is the combined probability of doing an addition and subtraction step. b is the balancing birth coefficient and d a balancing death coefficient. They are in place to set the ratio of birth step to death steps. Specifically,

$$b = \frac{A_{start}}{A_{start} + K_{start} + 1} \times \frac{1}{A}$$

$$d = \frac{K_{start}}{A_{start} + K_{start} + 1} \times \frac{1}{K}$$

The first fraction is based off of starting conditions and the second fraction changes through each step. We have that A_{start} is the starting number of available spaces. An available space is any data point that is not itself a breakpoint, and endpoint, or 2 points away from an existing breakpoint. K_{start} is the starting number of breakpoints that is proposed before the function is called.

2.3 AR model and draws

Once a step has been completed and a new breakpoint set is proposed then the data is fit using an auto-regressive model. With this information then we can get a draw of the β coefficients and σ.

2.4 Derivations of β and σ draws

The posterior for the β coefficient is laid out in detail in the *Forecasting time series* (Pesaran Paper, 2006). Given that b_0 is the mean of the βs, B_0 is the variance co-variance matrix of the βs for the prior. Also v_0 and d_0 are the parameters of the inverse gamma prior of the inverse gamma squared (one being the shape the other rate). While S_t is the current state of the break locations, and y_t is the actual data values.

$$\beta|\sigma^2, b_0, B_0, V_0, d_0, S_t, y_t \sim N(\overline{\beta_j}, \overline{V_j})$$

Where

$$\overline{V}_j = (\sigma^{-2}x^T x + B_0^{-1})^{-1}, \quad \overline{\beta}_j = \overline{V}_j(\sigma^{-2}x^T y_t + B_0^{-1}b_0)$$

The *Forecasting time series* (Pesaran Paper, 2006) also lays out the σ posterior such that

$$\sigma_j^{-2} \sim \Gamma(v_0, d_0) \longrightarrow \sigma_j^{-2}|\beta, b_0, B_0, v_0, d_0, S_t, y_t \sim \Gamma(\overline{v}_0, \overline{d}_0)$$

Where

$$\overline{v}_0 = v_0 + \frac{n_j}{2}, \quad \overline{d}_0 = d_0 + \frac{1}{2}(y_t - x\beta)^T(y_t - x\beta)$$

2.5 Simulation to evaluate

3 Results

4 Discussion

5 Appendix

Acknowledgements

We want to thank...