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Summary: Nonetheless the central role of the Box-Jenkis Gaussian autoregressive moving average models for continuous time series, there is no such a leading technique for count time series. In this paper we introduce a Bayesian nonparametric methodology for producing coherent predictions of a count time series $\{X_t\}$ using the nonnegative INteger-valued AutoRegressive process of the order 1 (INAR(1)) introduced by Al-Osh and Alzaid (1987) and McKenzie (1988). INAR models evolve as a birth-and-death process where the value at time t can be modeled as the sum of the survivors from time $t-1$ and the outcome of an innovation process with a certain discrete distribution. Obviously such components are not observable. Our predictions are based on estimates of the p-step ahead predictive mass functions assuming a nonparametric prior distribution for the innovation process. Precisely we model this distribution with a Dirichlet process mixture of rounded Gaussians (Canale and Dunson, 2011). This class of prior has large support on the space of probability mass functions and is able to generate almost any count distribution including over/under-dispersion or multimodality. An efficient Gibbs sampler is developed for posterior computation and the methodology is used to analyze real data sets.

Keywords: INAR(1), Dirichlet process mixtures, Gibbs sampling algorithm.

1. Introduction

Recently, there has been a growing interest in studying nonnegative integer-valued time series and, in particular, time series of counts. Examples are categorical time series, binary processes, birth-death models and counting series.

The most common approach to build an integer-valued autoregressive processes is using a probabilistic operation called thinning. Using binomial thinning, Al-Osh and Alzaid (1987) and McKenzie (1988) first introduced integer-valued autoregressive processes (INAR). A recent review on integer-valued AR processes can be found in Silva et al. (2005) and Jung and Tremayne (2011). While theoretical properties of INAR models have been extensively studied in the literature, relatively few contributions discuss the development of forecasting methods that are coherent, in the sense of producing only integer forecasts of the count variable. Freeland and McCabe (2004), in the context of INAR(1) process with Poisson innovations suggest some solutions that are somewhat problem-specific. Thus, McCabe and Martin (2005) consider the Bayesian point of view and present a methodology for producing coherent forecasts of low count time series that is completely general. The predictive probability mass function, defined only over the support of the discrete count variable, is a natural outcome of Bayes theorem.The results are valid for any sample size and not only asymptotically, moreover the innovations can be any arbitrary discrete distribution, within a specified finite set of distributions. In particular, the authors focus on Poisson, binomial and negative binomial distributions.

In this paper, we consider INAR(1) models with flexible specifications of the error term under a Bayesian nonparametric approach. The assumption of a nonparametric prior with large support for the innovation distribution, bypasses the need to specify a finite set of discrete distribution as in McCabe and Martin (2005). Our approach leads to two main improvements: first we overcome the specification of the predictive probability as a mixture of K predictive distributions, and second we do not rely on the usual strict parametric models. Among the different proposal made in the Bayesian nonparametric literature to model count distributions, we use that of Canale and Dunson (2011).

2. Model specification

To introduce the class of INAR model we first recall the thinning operator, '$\circ$', defined as follows.

Definition *Let Y be a non negative integer-valued random variable, then for any $\alpha \in [0,1]$*

$$\alpha \circ Y = \sum_{i=1}^{Y} X_i$$

where X_i is a sequence of iid count random variables, independent of Y, with common mean α.

The INAR(1) process $\{Y_t; t \in \mathbf{Z}\}$ is defined by the recursion

$$Y_t = \alpha \circ Y_{t-1} + \epsilon_t \tag{1}$$

where $\alpha \in [0,1]$, and ϵ_t is sequence of iid discrete random variables with finite first and second moment. The components of the process $\{Y_t\}$ are the surviving elements of the process Y_{t-1} during the period $(t-1,t]$, and the number of elements which entered the system in the same interval, ϵ_t. Each element of Y_{t-1} survives with probability α and its survival has no effect on the survival of the other elements, nor on ϵ_t which is not observed and cannot be derived from the Y process in the INAR(1) model. In the next section we discuss a nonparametric prior for the distribution of the error term.

To define a nonparametric model for counts, Canale and Dunson (2011) proposed to round an underlying variable having an unknown density given a Dirichlet process mixture of Gaussians prior. Such rounded mixture of Gaussians (RMG) have been showed to be highly flexible and having excellent performance in small samples while having appealing asymptotic properties in terms of large support and strong posterior consistency. Let the probability that the discrete error equals j, for $j \in \mathbf{N}$ to be

$$p(j) = g(f)[j] = \int_{a_j}^{a_{j+1}} f(y^*)dy^* \tag{2}$$

with the thresholds chosen as $a_0 = -\infty$ and $a_j = j-1$ for $j \in \{1,2,\dots\}$ and modelling the underlying f as the mixture model

$$f(y^*;P) = \int \phi(y^*;\mu,\tau^{-1})dP(\mu,\tau), \quad P \sim DP(\eta P_0). \tag{3}$$

Here, $\phi(y;\mu,\tau^{-1})$ is a Gaussian density having mean μ and precision τ and $DP(\eta P_0)$ corresponding to the Dirichlet process with P_0 chosen to be Normal-Gamma and $\eta > 0$. Equations (2)–(3) induce a prior $p \sim \Pi$ over $\mathcal{C}$, the space of the probability mass functions on the non negative integers.

3. *p-step ahead predictive probability mass function*

Exploiting the birth-and-death process interpretation of the INAR(1) model, the distribution of Y_t given y_{t-1}, α and p is

$$Pr(Y_t = y_t \mid y_{t-1},\alpha,p) = \sum_{s=0}^{\min\{y_t,y_{t-1}\}} Pr(B^{\alpha}_{y-1} = s) \times p(y_t - s) \tag{4}$$

where p is a random probability measure obtained through (2)–(3) and $B^{\pi}_{k} \sim \mathrm{Be}(k,\pi)$.

The likelihood function given $\mathbf{y} = (y_1,\dots,y_T)$ of α and the random discrete measure p turns out to be

$$\ell(\theta \mid \mathbf{y}) \quad \propto \quad \prod_{t=2}^{T} \sum_{s=0}^{\min\{y_t,y_{t-1}\}} \alpha^s(1-\alpha)^{y_{t-1}-s}p(y_t - s) \tag{5}$$

where $\theta \in \Theta$ and $\Theta = \mathbf{R} \times \mathcal{C}$. The posterior distribution can be obtained as

$$\pi(\theta \mid \mathbf{y}) \propto \ell(\theta \mid \mathbf{y})\pi(\theta) \tag{6}$$

where $\pi(\theta)$ is the prior probability. Given the nonparametric prior $p \sim \Pi$ it is sufficient to elicit a prior for $\alpha \sim \pi_\alpha$. In presence of prior information we can use a beta distribution with given mean corresponding to one's prior belief about α. Being noninformative one can assume a uniform prior distribution between zero and one. Assuming that α and p are independent a priori, the prior $\pi(\theta)$ is $\pi(\theta) = \Pi \times \pi_\alpha$.

The p-step ahead probability mass function is here defined as

$$Pr(Y_{T+p} = j \mid \mathbf{y}) = \int_\Theta Pr(Y_{T+p} = j \mid \mathbf{y}, \theta) d\pi(\theta \mid \mathbf{y}) \tag{7}$$

where $\pi(\theta \mid \mathbf{y})$ is the posterior distribution (6).

The following Gibbs sampler computes the quantity in (7) iterating the steps:

1. Data augmentation step given p and α.
   - For $t = 2, \dots, T$, simulate $B_t \sim \text{Be}(y_{t-1}, \alpha)$
   - For $t = 2, \dots, T$, simulate $\epsilon_t^* \sim f$ where f is as in (2)–(3) under the constraints $a_{y_t - B_t} \leq \epsilon_t^* \leq a_{y_t - B_t + 1}$
2. Update the parameters of the RMG as in Canale and Dunson (2011)
3. Update α from its conditional posterior distribution via Metropolis-Hastings step
4. After burn in, simulate Y_{t+p} as in equation (4)

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