

# Gamma AR Processes with Variable Shape

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## Introduction

Following the construction of Sim (1990), we consider a model autoregressive gamma model of the following form:

$$X_n = \alpha * X_{n-1} + \varepsilon_n, \quad \text{where} \quad \alpha * X_{n-1} = \sum_{i=0}^{N(X)} W_i$$

In the above,

- $\varepsilon_n \sim \text{Gamma}(\nu, \alpha)$  with (unintuitively) **shape**  $\nu$  and **scale**  $\alpha$ .
- Each  $W_i$  are *iid* exponential random variables with rate  $\alpha$
- For a fixed value of  $x$ , the  $N(x)$  is a Poisson distributed random variable with rate parameter  $\lambda = p\alpha$
- Where  $p$  indicates the magnitude of the autocorrelation in the process

## Allowing Temporal Dependence in Shape

We now consider the case where the shape parameter  $\nu$  is unique for each  $X_n$ ; as such, it is temporally dependent and potentially a function of other random variables, i.e.  $\nu \rightarrow \nu_n$ , for  $n > 0$ .

### Derivations 2.1.1, 2.1.2, 2.2

We begin by noting that the Laplace transform (LT) of  $\alpha * X$  conditioned on a fixed  $X = x$  (derivations 2.1.1 and 2.1.2) remain unchanged, as both  $W_i$  and  $N(X)$  are independent of  $\nu_t$ .

From this independence, the cumulative process  $\alpha * X_{n-1}$  remains independent of  $\varepsilon_t$ . Thus the LT of  $X_n$  given  $X_{n-1} = x$  can be written as a slight adjustment of the previously-derived Equation 2.2., i.e.

$$\mathbb{E}[\exp(-sX_n) \mid X_{n-1} = x] = \left(\frac{\alpha}{s + \alpha}\right)^{\nu_t} \exp\left(\frac{-\lambda xs}{\alpha + s}\right)$$

As before, allowing  $\Phi_{X_n}(s)$  to be the Laplace transform of the PDF of  $X_n$  (i.e.  $\Phi_{X_n}(s) = \mathbb{E}[\exp(-sX_n)]$ ), yields

$$\Phi_{X_n}(s) = \left(\frac{\alpha}{s + \alpha}\right)^{\nu_n} \Phi_{X_{n-1}}\left(\frac{\alpha ps}{\alpha + s}\right)$$

## Derivation 2.2.2: The Trouble Point

Previously, we solved the recursive relationship for  $\Phi_{X_n}(s)$  to prove that  $\Phi_{X_n}(s) \rightarrow (1 + \theta^{-1})^{-\nu}$  as  $n \rightarrow \infty$ .

In order to do this, we recognized and simplified a telescoping series that allowed us to write:

$$\Phi_{X_n}(s) = \left( \frac{\alpha}{\alpha + s \sum_{k=0}^{n-1} p^k} \right)^\nu \Phi_{X_0} \left( \frac{\alpha p^n s}{\alpha + s \sum_{k=0}^{n-1} p^k} \right)$$

In my proof of this, I wrote up a generalized  $n = 2$  case and noticed the emerging pattern. However, in my rough work I also derived the  $n = 3$  instance to identify the telescoping properties. Specifically, letting  $C_2$  be the coefficients of  $\Phi_{X_2}(s)$  I had that

$$\begin{aligned} \Phi_{X_3}(s) &= C_2 \cdot \Phi_{X_1} \left( \frac{\alpha p^2 s}{\alpha + p(1-s)} \right) \\ &= C_2 \cdot \left( \frac{\alpha}{\alpha + \frac{\alpha p^2 s}{\alpha + p(1-s)}} \cdot \Phi_{X_0}(\dots) \right)^\nu \\ &= C_2 \left( \frac{\alpha + p(1+s)}{\alpha + p^2 s + ps + p} \right)^\nu \\ &= \left( \frac{\alpha}{\alpha + s} \right)^\nu \left( \frac{\alpha + s}{\alpha + p(1+s)} \right)^\nu \left( \frac{\alpha + p(1+s)}{\alpha + p^2 s + ps + p} \right)^\nu \Phi_0(\dots) \end{aligned} \quad (\star)$$

The telescoping pattern in  $(\star)$  allows us to simplify the pattern for general  $n$  to a geometric sum in which  $\Phi_0(\dots)$  becomes negligible as  $n \rightarrow \infty$ . However, if we allow for different values of  $\nu$  for each  $n$ , the series cannot simplify in this fashion.

Instead, it becomes some strange non-simplifying product sequence.

$$\begin{aligned} \Phi_{X_3} &= \left( \frac{\alpha}{\alpha + s} \right)^{\nu_1} \left( \frac{\alpha + s}{\alpha + p(1+s)} \right)^{\nu_2} \left( \frac{\alpha + p(1+s)}{\alpha + p^2 s + ps + p} \right)^{\nu_3} \Phi_0(\dots) \\ &= \alpha^{\nu_1} (\alpha + s)^{\nu_2 - \nu_1} (\alpha + p(1+s))^{\nu_3 - \nu_2} (\alpha + p^2 + ps + p)^{-\nu_3} \end{aligned}$$

So then the general form would be something like this (omitting the  $\Phi_0(\dots)$  contribution for simplicity):

$$\Phi_{X_n}(s) \propto \alpha^{\nu_1} P_n^{-\nu_n} \prod_{k=1}^{n-1} P_k^{\nu_k - \nu_{k+1}}, \text{ where } P_k = \alpha + p + s \sum_{m=1}^{k-1} p^m$$

Since  $\nu_k - \nu_{k+1} \neq 0$  by assumption of time-varying shape terms, the product does not reduce to a gamma distribution form (although it may converge), and hence we cannot write  $\Phi_{X_n}(s)$  as a Gamma distribution as  $n \rightarrow \infty$ .

## Variable Scale

Similarly to earlier, should we allow the scale to vary with time, i.e.  $\alpha \rightarrow \alpha_t$ , there are a few notable changes.

Firstly, for a fixed  $X_n = x$  we still have:

$$\{\mathcal{L}_{\alpha_n * X}^*\}(s) = \exp\left(-\frac{p\alpha_n x s}{\alpha_n + s}\right)$$

However, this is now dependent on  $\alpha_n$ , implying that

$$\begin{aligned} \mathbb{E}[\exp(-sX_n) \mid X_{n-1} = x] &= \mathbb{E}[\exp(-s\varepsilon_n)] \mathbb{E}[-(\alpha * X_{n-1}) \mid X_{n-1} = x] \\ &= \left( \frac{\alpha_n}{s + \alpha_n} \right)^\nu \exp\left(\frac{-p\alpha_{n-1} x s}{\alpha_{n-1} + s}\right) \end{aligned}$$

Thus, the LT of the unconditional PDF of  $X_n$  (Derivation 2.2.2) faces a similar problem to before, since

$$\Phi_{X_n}(s) = \left(\frac{\alpha_n}{s + \alpha_n}\right)^\nu \Phi_{X_{n-1}}\left(\frac{p\alpha_{n-1}s}{\alpha_{n-1} + s}\right)$$

Which means that upon solving recursively (for, say,  $n = 2$ ) we have:

$$\begin{aligned} \Phi_{X_2}(s) &= \left(\frac{\alpha_2}{s + \alpha_2}\right)^\nu \Phi_{X_1}\left(\frac{p\alpha_1s}{\alpha_1 + s}\right) \\ &= \left(\frac{\alpha_2}{s + \alpha_2}\right)^\nu \left[ \left(\frac{\alpha_1}{\frac{p\alpha_1s}{\alpha_1+s} + \alpha_1}\right)^\nu \Phi_{X_0}\left(\frac{\alpha_0 p \frac{p\alpha_1s}{\alpha_1+s}}{\alpha_0 + \frac{p\alpha_1s}{\alpha_1+s}}\right) \right] \\ &= \left(\frac{\alpha_2}{s + \alpha_2}\right)^\nu \left(\frac{\alpha_1 + s}{\alpha_1 + s + ps}\right)^\nu \Phi_{X_0}\left(\frac{\alpha_0 \alpha_1 p^2 s}{\alpha_0 \alpha_1 + \alpha_0 s + p\alpha_1 s}\right) \end{aligned}$$

Notice that the third term in the product  $\Phi_{X_0}(\dots)$  doesn't simplify as nicely as before. Because  $\alpha_1 \neq \alpha_0$ , we cannot factor out the  $\alpha$  term as we did before.

This means that in the  $n \geq 3$  cases we lose the telescoping property.

$$\Phi_{X_3}(s) = \left(\frac{\alpha_3}{s + \alpha_3}\right)^\nu \left(\frac{\alpha_2 + s}{\alpha_2 + s + ps}\right)^\nu \left(\frac{\alpha_1 \alpha_2 + \alpha_2 p^2 s + \alpha_1 s + p\alpha_2}{\alpha_1 \alpha_2 + \alpha_1 s + p\alpha_2 s}\right)^\nu \Phi_{X_0}(\dots)$$

Thus, this form doesn't converge to a Gamma distribution, either.

## Which Factors Still Hold?

If we allow  $\nu$  to vary with time, the LT of the PDF of the conditional density of  $X_n$  remains

$$\{\mathcal{L}_{X_n|X_{n-1}}^*\}(s) = \mathbb{E}[\exp(-sX_n) | X_{n-1} = x] = \left(\frac{\alpha}{s + \alpha}\right)^{\nu_n} \exp\left(\frac{-p\alpha xs}{\alpha + s}\right)$$

From this, we could theoretically compute the inverse Laplace transform and construct a log-likelihood function

$$\ell(\theta; x_0, x_1, \dots, x_n) \propto \sum_{t=1}^n \log(\{\mathcal{L}_{X_n|X_{n-1}}^*(s)\}^{-1}) = \sum_{t=1}^n f_{X_t|X_{t-1}}(x_t | x_{t-1})$$

However, in doing this we could not admit that our  $X_t$  are Gamma-distributed. We could allow  $X_t$  to be our DKR process, and consider this

## Conclusion

Since neither adjustment converges  $X_n$  to a Gamma distribution, the subsequent derivations and properties will not hold either. Further, we cannot use it for our DKR model by the lack of Gamma-distributed  $X_n$ , which we had intended to equate our model to one of the coefficients with.