# ON CALCULATION OF STATIONARY DENSITY OF AUTOREGRESSIVE PROCESSES 

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An iterative procedure for computation of stationary density of autoregressive processes is proposed. On an example with exponentially distributed white noise it is demonstrated that the procedure converges geometrically fast. The $\operatorname{AR}(1)$ and $\operatorname{AR}(2)$ models are analyzed in detail.

## 1. INTRODUCTION AND PRELIMINARIES

Let $\left\{X_{t}\right\}$ be a stationary autoregressive process of the first order defined by

$$
\begin{equation*}
X_{t}=b X_{t-1}+e_{t}, \quad 0 \neq b \in(-1,1) \tag{1.1}
\end{equation*}
$$

where $\left\{e_{t}\right\}$ are i.i.d. random variables with a finite second moment. From (1.1) we have

$$
\begin{equation*}
X_{t}=e_{t}+b e_{t-1}+b^{2} e_{t-2}+\ldots \tag{1.2}
\end{equation*}
$$

and the series converges in the quadratic mean. It is clear from (1.2) that $\left\{X_{t}\right\}$ is strictly stationary. We are interested in the stationary distribution of the process $\left\{X_{t}\right\}$. The following assertions show that this distribution is continuous.

Theorem 1.1. Let $\left\{\xi_{t}\right\}$ be i.i.d. random variables. If the series $X=\sum_{t=-\infty}^{\infty} k_{t} \xi_{t}$ converges almost surely and infinite many $k_{t}$ are different from 0 then $X$ has a continuous distribution.

Proof. See [10].

Theorem 1.2. Let $\left\{\eta_{t}\right\}$ be independent random variables such that $E \eta_{t}^{2}<\infty$ and $\sum \operatorname{var} \eta_{t}<\infty$. Then the series $\sum\left(\eta_{t}-E \eta_{t}\right)$ converges almost surely.

Proof. See [15], § 16.2 and $\S 17.2$, or [18], Theorem IV.1.4, p. 241.

Theorem 1.3. The stationary distribution of the process $\left\{X_{t}\right\}$ defined by (1.1) is continuous.

Proof. The assertion is a direct consequence of Theorems 1.1 and 1.2.

For example, if $b=0.5$ and $e_{t}$ is a discrete random variable such that $P\left(e_{t}=\right.$ $0.5)=P\left(e_{t}=-0.5\right)=0.5$ then $X_{t}$ has the continuous rectangular distribution $R(-1,1)$. A review of some results of this kind can be found in [2].

However, in many cases stronger assumptions about $e_{t}$ are made.
Theorem 1.4. If $e_{t}$ has a density, then $X_{t}$ has also a density.
Proof. Using (1.2) we can write $X_{t}=e_{t}+Z_{t}$ where $Z_{t}=b e_{t-1}+b^{2} e_{t-2}+\ldots$ Since $e_{t}$ and $Z_{t}$ are independent and $e_{t}$ has a density, their sum $e_{t}+Z_{t}=X_{t}$ has an absolutely continuous distribution (see [16], p. 196).

Now, we introduce a known equation for the stationary distribution of $X_{t}$ and a formula for the characteristic function of $X_{t}$.

Theorem 1.5. Let $e_{t}$ have a density $f$. Then the density $h$ of $X_{t}$ satisfies the equation

$$
\begin{equation*}
h(x)=\int f(x-b u) h(u) \mathrm{d} u \tag{1.3}
\end{equation*}
$$

Proof. The equation follows from (1.1), since $X_{t-1}$ has also the density $h$ and $X_{t-1}$ and $e_{t}$ are independent.

Theorem 1.6. Let $\psi(t)$ be the characteristic function of $e_{t}$ and let $\rho(t)$ be the characteristic function of $X_{t}$. Then

$$
\rho(t)=\prod_{n=0}^{\infty} \psi\left(b^{n} t\right)
$$

Proof. Define

$$
\begin{equation*}
Y_{t, n}=e_{t}+b e_{t-1}+\ldots+b^{n} e_{t-n} \tag{1.4}
\end{equation*}
$$

Then $Y_{t, n} \rightarrow X_{t}$ in the quadratic mean as $n \rightarrow \infty$. Thus $Y_{t, n} \rightarrow X_{t}$ also in the distribution. It implies that the characteristic functions of the variables $Y_{t, n}$ converge pointwise to $\rho(t)$. But the characteristic function of $Y_{t, n}$ is $\psi(t) \psi(b t) \ldots \psi\left(b^{n} t\right)$.

If $e_{t}$ has normal distribution then it is well known that $X_{t}$ is also normally distributed. One of the first attempts to find a connection between the distributions of $X_{t}$ and $e_{t}$ in a non-normal case was published in [9]. For some special nonnormal distributions of $e_{t}$ (continuous and discrete rectangular distributions, Laplace distribution) the stationary distribution of $X_{t}$ is calculated in [2]. It is also known
that if $e_{t}$ has a stable distribution of exponent $\theta,(0<\theta \leq 2)$ then $X_{t}$ also has a stable distribution of the same exponent (e.g., see [19], p. 208, Ex. 11).

By the way, the opposite problem was more popular, viz. to find a distribution of $e_{t}$ for a given stationary distribution of $X_{t}$. The famous paper [12] contains the cases when $X_{t}$ has exponential or gamma distributions. A review of such results can be found in [1] and [2].

The methods mentioned above were applicable only to some special distributions of $X_{t}$ and $e_{t}$. Another approach was proposed in [3]. The goal of this paper was to find a distribution of $e_{t}$ such that the stationary distribution of $X_{t}$ has given moments. This method was derived for general linear processes so that autoregressive models form only a special class. Detailed results for $\operatorname{AR}(1)$ models are published in [4]. A different method based on Hermite polynomials can be found in [17].

The problem how to calculate stationary distribution of a process from the distribution of a white noise seems to be even more popular in non-linear models. The method of moments was applied in [6]. Exact explicit results are quite rare. One of them can be found in [7] but formulas for stationary density of the absolute autoregression published in [8] and [5] became more familiar (cf. [19], pp. 140-142 and p.205). Numerical procedures suggested for computation of stationary density in non-linear models (see [19], p.152) can be, of course, also used in the model (1.1). It corresponds to numerical solution of the equation (1.3).

Quite recently (see [13]) some theoretic results for the stationary density of $X_{t}$ in the model (1.1) were derived in the case that $e_{t}$ has the rectangular distribution on ( 0,1 ). It was proved that the stationary density belongs to the class $C^{\infty}$ and some bounds for tails of this stationary distribution were derived. The derivation was based on investigation of asymptotic properties of $e_{t}+b e_{t-1}+\cdots+b^{n} e_{t-n}$ as $n \rightarrow \infty$.

## 2. AN ITERATIVE METHOD FOR AR(1) PROCESSES

An explicit formula for $h$ satisfying (1.3) given $f$ is known only in a few cases. Here we propose an iterative method for its computation. Let $h_{0}$ be an arbitrary density. For $n \geq 1$ define

$$
\begin{equation*}
h_{n}(x)=\int f(x-b u) h_{n-1}(u) \mathrm{d} u \tag{2.1}
\end{equation*}
$$

It is obvious that every function $h_{n}$ defined by (2.1) is a density.

Theorem 2.1. Let $h_{0}$ be a density. Define $h_{n}$ by (2.1). Assume that there exists an integer $m \geq 0$ such that

$$
\begin{equation*}
\int_{-\infty}^{\infty}\left|\psi(t) \psi(b t) \ldots \psi\left(b^{m} t\right)\right| \mathrm{d} t<\infty \tag{2.2}
\end{equation*}
$$

Then $h_{n}(x) \rightarrow h(x)$ for all $x$ as $n \rightarrow \infty$.

Proof. Let $\lambda_{n}$ be the characteristic function corresponding to $h_{n}$. Using (2.1) we obtain

$$
\begin{aligned}
\lambda_{n}(t) & =\int e^{i t x} h_{n}(x) \mathrm{d} x=\int e^{i t x}\left[\int f(x-b u) h_{n-1}(u) \mathrm{d} u\right] \mathrm{d} x \\
& =\int h_{n-1}(u)\left[\int e^{i t x} f(x-b u) \mathrm{d} x\right] \mathrm{d} u=\int h_{n-1}(u)\left[\int e^{i t b u+i t y} f(y) \mathrm{d} y\right] \mathrm{d} u \\
& =\psi(t) \int e^{i t b u} h_{n-1}(u) \mathrm{d} u=\psi(t) \lambda_{n-1}(b t)
\end{aligned}
$$

Thus

$$
\lambda_{n}(t)=\psi(t) \psi(b t) \psi\left(b^{2} t\right) \ldots \psi\left(b^{n-1} t\right) \lambda_{0}\left(b^{n} t\right)
$$

From the continuity of the characteristic function we have

$$
\lambda_{0}\left(b^{n} t\right) \rightarrow \lambda_{0}(0)=1 \quad \text { as } n \rightarrow \infty
$$

Using Theorem 1.6 we get $\lambda_{n}(t) \rightarrow \rho(t)$ as $n \rightarrow \infty$. Assume that $n>m$. Because

$$
\begin{equation*}
h_{n}(x)=\frac{1}{2 \pi} \int_{-\infty}^{\infty} e^{-i t x} \lambda_{n}(t) \mathrm{d} t \tag{2.3}
\end{equation*}
$$

and $\left|e^{-i t x} \lambda_{n}(t)\right| \leq\left|\psi(t) \psi(b t) \ldots \psi\left(b^{m} t\right)\right|$, Lebesgue theorem gives

$$
\lim _{n \rightarrow \infty} h_{n}(x)=\frac{1}{2 \pi} \int_{-\infty}^{\infty} e^{-i t x}\left[\lim _{n \rightarrow \infty} \lambda_{n}(t)\right] \mathrm{d} t=\frac{1}{2 \pi} \int_{-\infty}^{\infty} e^{-i t x} \rho(t) \mathrm{d} t=h(x)
$$

Of course, speed of the convergence and complexity of formulas for $h_{n}$ depend heavily on the choice of $h_{0}$.

## 3. AN EXAMPLE

Sometimes it is easy to derive speed of convergence $h_{n}(x) \rightarrow h(x)$. From (2.3) we have

$$
\left|h_{n+1}(x)-h_{n}(x)\right| \leq \frac{1}{2 \pi} \int_{-\infty}^{\infty}\left|\lambda_{n+1}(t)-\lambda_{n}(t)\right| \mathrm{d} t
$$

Define

$$
\Delta_{n+1}=\sup _{x}\left|h_{n+1}(x)-h_{n}(x)\right|
$$

Then we get

$$
\begin{equation*}
\Delta_{n+1} \leq \frac{1}{2 \pi} \int_{-\infty}^{\infty}\left|\psi(t) \psi(b t) \ldots \psi\left(b^{n-1} t\right)\left[\psi\left(b^{n} t\right) \lambda_{0}\left(b^{n+1} t\right)-\lambda_{0}\left(b^{n} t\right)\right]\right| \mathrm{d} t \tag{3.1}
\end{equation*}
$$

Consider the process $\left\{X_{t}\right\}$ given by (1.1) such that $b \in(0,1)$ and $e_{t} \sim E x(1)$, i. e., $f(x)=e^{-x}$ for $x>0$. For simplicity, choose $h_{0}(x)=f(x)$. Then

$$
\psi(t)=\lambda_{0}(t)=\frac{1}{1-i t}
$$

Since

$$
\begin{equation*}
|\psi(t)|=\frac{1}{\sqrt{1+t^{2}}} \tag{3.2}
\end{equation*}
$$

the assumption (2.2) is fulfilled for $m=1$. The inequality (3.1) can be written in the form

$$
\begin{equation*}
\Delta_{n+1} \leq \int_{-\infty}^{\infty}\left|\left[\prod_{s=0}^{n} \psi\left(b^{s} t\right)\right]\left[\psi\left(b^{n+1} t\right)-1\right]\right| \mathrm{d} t \tag{3.3}
\end{equation*}
$$

Assume that $n \geq 3$. Then (3.3) and (3.2) yield

$$
\begin{aligned}
\Delta_{n+1} & \leq \frac{1}{\pi} \int_{-\infty}^{\infty}|\psi(t) \psi(b t)| \cdot\left|\psi\left(b^{2} t\right) \psi\left(b^{3} t\right)\right| \cdot\left|\psi\left(b^{n+1} t\right)-1\right| \mathrm{d} t \\
& \leq \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{1}{1+b^{2} t^{2}} \frac{1}{1+b^{6} t^{2}} \frac{b^{n+1} t}{\sqrt{1+b^{2 n+2} t^{2}}} \mathrm{~d} t \\
& \leq b^{n+1} \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{1}{1+b^{2} t^{2}} \frac{1}{1+b^{6} t^{2}} \mathrm{~d} t
\end{aligned}
$$

Since

$$
\frac{t}{1+b^{6} t^{2}} \leq \frac{1}{2 b^{3}}, \quad \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{\mathrm{d} t}{1+b^{2} t^{2}}=\frac{1}{2 b}
$$

we have

$$
\Delta_{n+1} \leq \frac{1}{4} b^{n-3}
$$

In this case the iterative procedure converges to the limit density geometrically fast.
For small values of $n$ we write (3.3) in the form

$$
\Delta_{n+1} \leq \frac{b^{n+1}}{\pi} \int_{0}^{\infty} t \prod_{s=0}^{n+1}\left(1+b^{2 s} t^{2}\right)^{-1 / 2} \mathrm{~d} t
$$

Especially,

$$
\begin{aligned}
\Delta_{2} & \leq \frac{b^{2}}{\pi} \int_{0}^{\infty} t \frac{1}{\sqrt{1+t^{2}}} \frac{1}{\sqrt{1+b^{2} t^{2}}} \frac{1}{\sqrt{1+b^{4} t^{2}}} \mathrm{~d} t \\
& \leq \frac{b^{2}}{\pi} \int_{0}^{\infty} \frac{t}{\left(1+b^{4} t^{2}\right) \sqrt{1+t^{2}}} \mathrm{~d} t=\frac{b^{2}}{2 \pi} \int_{0}^{\infty} \frac{\mathrm{d} x}{\left(1+b^{4} x\right) \sqrt{1+x}} \\
& =\frac{\pi-2 \operatorname{arctg} \frac{b^{2}}{\sqrt{1-b^{4}}}}{2 \pi \sqrt{1-b^{4}}}=D_{2}(b)
\end{aligned}
$$

Similarly,

$$
\begin{aligned}
\Delta_{3} & \leq \frac{b^{3}}{\pi} \int_{0}^{\infty} \frac{t}{\sqrt{1+t^{2}}} \frac{1}{\sqrt{1+b^{2} t^{2}}} \frac{1}{\sqrt{1+b^{4} t^{2}}} \frac{1}{\sqrt{1+b^{6} t^{2}}} \mathrm{~d} t \\
& \leq \frac{b^{3}}{\pi} \int_{0}^{\infty} \frac{1}{1+b^{2} t^{2}} \frac{1}{1+b^{6} t^{2}} \mathrm{~d} t=-\frac{2 b \ln b}{\pi\left(1-b^{4}\right)}=D_{3}(b)
\end{aligned}
$$

Some values of $D_{2}(b)$ and $D_{3}(b)$ are introduced in Table 3.1.


Fig. 3.1.

Table 3.1.

| $b$ | 0.01 | 0.1 | 0.5 | 0.9 | 0.99 |
| :---: | :--- | :--- | :--- | :--- | :--- |
| $D_{2}(b)$ | 0.50 | 0.50 | 0.43 | 0.34 | 0.32 |
| $D_{3}(b)$ | 0.03 | 0.15 | 0.24 | 0.18 | 0.16 |

Explicit formulas for $h_{n}(x)$ can be written down if $n$ is small. For example,

$$
\begin{aligned}
h_{1}(x) & =\frac{e^{-x}}{1-b}\left(1-e^{x-x / b}\right) \\
h_{2}(x) & =\frac{e^{-x}}{(1-b)^{2}}\left[1-e^{x-x / b}-\frac{b-e^{x\left(b^{2}+b-1\right) / b-1 / b}}{1+b}\right]
\end{aligned}
$$

and so on. However, it is easier to use a program package for calculating and processing the functions $h_{n}(x)$. We used Mathematica. Figure 3.1 shows functions $h_{0}(x), \ldots, h_{5}(x)$ in the case $b=0.5$.

## 4. A GENERALIZATION TO AR PROCESSES OF HIGHER ORDER

The iterative method for calculating stationary density can be generalized to autoregressive processes of higher order. Here we present a derivation for AR(2) model.

Let $X_{t}$ be a stationary AR(2) process defined by

$$
\begin{equation*}
X_{t}=b_{1} X_{t-1}+b_{2} X_{t-2}+e_{t} \tag{4.1}
\end{equation*}
$$

where $e_{t}$ is a strict white noise with a density $f$ and a finite second moment. Let $\psi$ be the characteristic function of $e_{t}$ and

$$
\boldsymbol{F}=\left(\begin{array}{cc}
b_{1} & b_{2} \\
1 & 0
\end{array}\right)
$$

It is known that

$$
X_{t}=\sum_{j=0}^{\infty} a_{j} e_{t-j}
$$

where $a_{j}$ is the (1,1)-element of the matrix $F^{j}$ (see [14], p. 57). It follows from the assumption of stationarity that all roots of $\boldsymbol{F}$ lie inside the unit circle and thus the series (4.1) converges in the quadratic mean. If we define $\boldsymbol{c}=(1,0)^{\prime}$ then $a_{j}=\boldsymbol{c}^{\prime} \boldsymbol{F}^{\boldsymbol{j}} \boldsymbol{c}=\boldsymbol{c}^{\boldsymbol{\prime}} \boldsymbol{F}^{\prime \boldsymbol{j}} \boldsymbol{c}$ and the characteristic function $\lambda$ of $X_{t}$ is given by

$$
\begin{equation*}
\lambda(v)=\prod_{j=0}^{\infty} \psi\left(v a_{j}\right)=\prod_{j=0}^{\infty} \psi\left(v \boldsymbol{c}^{\prime} \boldsymbol{F}^{\prime j} \boldsymbol{c}\right) \tag{4.2}
\end{equation*}
$$

Since we assume that $e_{t}$ has a density, it follows from (4.1) that the random vector $\left(X_{t}, X_{t-1}\right)^{\prime}$ has a joint density, say $q(x, y)$. The stationary density of $\left\{X_{t}\right\}$ is $\int q(x, y) \mathrm{d} y$. Because $\left\{X_{t}\right\}$ is stationary, the vector $\left(X_{t-1}, X_{t-2}\right)^{\prime}$ has also the density $q$. The joint density of $\left(X_{t}, X_{t-1}, X_{t-2}\right)^{\prime}$ is $q\left(x_{t-1}, x_{t-2}\right) f\left(x_{t}-b_{1} x_{t-1}-b_{2} x_{t-2}\right)$ and so we have an integral equation

$$
\begin{equation*}
q\left(x_{t}, x_{t-1}\right)=\int q\left(x_{t-1}, x_{t-2}\right) f\left(x_{t}-b_{1} x_{t-1}-b_{2} x_{t-2}\right) \mathrm{d} x_{t-2} \tag{4.3}
\end{equation*}
$$

Let $q_{0}(y, z)$ be a density. Formula (4.3) suggests that a method for calculating $q$ can be based on the recurrent relation

$$
\begin{equation*}
q_{n}(x, y)=\int q_{n-1}(y, z) f\left(x-b_{1} y-b_{2} z\right) \mathrm{d} z \tag{4.4}
\end{equation*}
$$

We prove that under some conditions concerning $q_{0}$ the functions $q_{n}$ converge pointwise to $q$.

Theorem 4.1. Let $\lambda_{n}$ be the characteristic function corresponding to $q_{n}$. Then for arbitrary $t=\left(t_{1}, t_{2}\right)^{\prime}$ we have $\lambda_{n}(t) \rightarrow \lambda(t)$.

Proof. Using (4.4) we get

$$
\begin{aligned}
\lambda_{n}\left(t_{1}, t_{2}\right) & =\iint e^{i t_{1} x+i t_{2} y} q_{n}(x, y) \mathrm{d} x \mathrm{~d} y \\
& =\iiint e^{i t_{1} x+i t_{2} y} q_{n-1}(y, z) f\left(x-b_{1} y-b_{2} z\right) \mathrm{d} z \mathrm{~d} x \mathrm{~d} y
\end{aligned}
$$

$$
\begin{aligned}
& =\iiint e^{i t_{1}\left(w+b_{1} y+b_{2} z\right)+i t_{2} y} q_{n-1}(y, z) f(w) \mathrm{d} z \mathrm{~d} w \mathrm{~d} y \\
& =\iint e^{i\left(t_{1} b_{1}+t_{2}\right) y+i t_{1} b_{2} z} q_{n-1}(y, z) \mathrm{d} y \mathrm{~d} z \int e^{i t_{1} w} f(w) \mathrm{d} w \\
& =\lambda_{n-1}\left(t_{1} b_{1}+t_{2}, t_{1} b_{2}\right) \psi\left(t_{1}\right) \\
& =\lambda_{n-1}\left(\boldsymbol{F}^{\prime} \boldsymbol{t}\right) \psi\left(\boldsymbol{c}^{\prime} \boldsymbol{t}\right)
\end{aligned}
$$

This gives

$$
\lambda_{n}(\boldsymbol{t})=\psi\left(\boldsymbol{c}^{\prime} \boldsymbol{t}\right) \psi\left(\boldsymbol{c}^{\prime} \boldsymbol{F}^{\prime} \boldsymbol{t}\right) \ldots \psi\left(\boldsymbol{c}^{\prime} \boldsymbol{F}^{\prime n-1} \boldsymbol{t}\right) \lambda_{0}\left(\boldsymbol{F}^{\prime n} \boldsymbol{t}\right)
$$

Since $\boldsymbol{F}^{n} \rightarrow \mathbf{0}$ as $n \rightarrow \infty$, we have $\lambda_{0}\left(\boldsymbol{F}^{\prime n} \boldsymbol{t}\right) \rightarrow 1$ and in view of (4.2) it follows that $\lambda_{n}(t) \rightarrow \lambda(t)$.

Theorem 4.2. Let $q_{0}$ be a density. Assume that there exists an integer $m \geq 0$ such that

$$
\iint\left|\psi\left(\boldsymbol{c}^{\prime} \boldsymbol{t}\right) \psi\left(\boldsymbol{c}^{\prime} \boldsymbol{F}^{\prime} \boldsymbol{t}\right) \ldots \psi\left(\boldsymbol{c}^{\prime} \boldsymbol{F}^{\prime m} \boldsymbol{t}\right)\right| \mathrm{d} t_{1} \mathrm{~d} t_{2}<\infty
$$

Then $q_{n}(x, y) \rightarrow q(x, y)$ for all $(x, y)$ as $n \rightarrow \infty$.
Proof. For $n \geq m$ we have

$$
\left|\lambda_{n}\left(t_{1}, t_{2}\right)\right| \leq\left|\psi\left(\boldsymbol{c}^{\prime} \boldsymbol{t}\right) \psi\left(\boldsymbol{c}^{\prime} \boldsymbol{F}^{\prime} \boldsymbol{t}\right) \ldots \psi\left(\boldsymbol{c}^{\prime} \boldsymbol{F}^{\prime m} \boldsymbol{t}\right)\right|
$$

and thus $\iint\left|\lambda_{n}\left(t_{1}, t_{2}\right)\right| \mathrm{d} t_{1} \mathrm{~d} t_{2}<\infty$. Then $q_{n}(x, y)$ is bounded, continuous, and

$$
q_{n}(x, y)=\frac{1}{(2 \pi)^{2}} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{-i\left(x t_{1}+y t_{2}\right)} \lambda_{n}\left(t_{1}, t_{2}\right) \mathrm{d} t_{1} \mathrm{~d} t_{2}
$$

(see [11], formula 7.12). Theorem 4.1 and Lebesgue theorem imply

$$
\lim _{n \rightarrow \infty} \frac{1}{(2 \pi)^{2}} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{-i\left(x t_{1}+y t_{2}\right)} \lambda_{n}\left(t_{1}, t_{2}\right) \mathrm{d} t_{1} \mathrm{~d} t_{2}=q(x, y)
$$

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