

Solution to Exercise 3

Simon A. Broda

1. (a) We clearly see that unless $|\phi_1|$ approaches 1, the process is stationary; the time series plot looks mean-reverting, and the sample autocorrelations decay exponentially as they should. We also see that \bar{y} is close to $\mathbb{E}[Y_t] = \alpha/(1 - \phi_1)$, and that s_y^2 is close to $\text{var}[Y_t] = \sigma^2/(1 - \phi_1^2)$.
 (b) If $\phi_1 = 1$, we have a random walk, and α becomes the drift: $\mathbb{E}[Y_t] = Y_0 + \alpha \cdot t$.
 (c) See Jupyter notebook.
2. See Jupyter notebook.
3. (a) By repeatedly plugging in,

$$\begin{aligned}
 Y_t &= \alpha + Y_{t-1} + U_t \\
 &= \alpha + (\alpha + Y_{t-2} + U_{t-1}) + U_t \\
 &\vdots \\
 &= Y_0 + \alpha \cdot t + \sum_{s=1}^t U_s,
 \end{aligned}$$

so that

$$\mathbb{E}[Y_t] = Y_0 + \alpha \cdot t,$$

because white noise has expectation zero. The derivation of the variance is the same as for the case without drift from last week and thus omitted here.

- (b) The previous question shows that the random walk with drift is not stationary, because its mean and variance change over time. For it to be I(1), its first difference ΔY_t should be stationary. We immediately see that $\Delta Y_t = Y_t - Y_{t-1} = (\alpha + Y_{t-1} + U_t) - Y_{t-1} = \alpha + U_t$. This is just white noise plus a constant, which is stationary.
- (c) Since $\{U_t\}$ is white noise, U_t is uncorrelated with Y_{t-1} , so

$$\begin{aligned}
 \text{var}(Y_t) &= \text{var}(\alpha + \phi_1 Y_{t-1} + U_t) \\
 &= \phi_1^2 \text{var}(Y_{t-1}) + \text{var}(U_t) + 2\phi_1 \text{cov}(Y_{t-1}, U_t) = \phi_1^2 \text{var}(Y_t) + \sigma^2,
 \end{aligned}$$

where the final equality holds because Y_t is stationary, which implies that $\text{var}(Y_t) = \text{var}(Y_{t-1})$. Thus, if and only if $|\phi_1| < 1$,

$$\text{var}(Y_t) = \frac{\sigma^2}{1 - \phi_1^2}.$$

Note that $\text{var}(Y_t) > \text{var}(Y_{t-1})$ if $|\phi_1| \geq 1$, i.e., the variance grows without bounds in that case.

(d) **Optional:** For the MA(1) process

$$Y_t = \alpha + U_t + \theta_1 U_{t-1},$$

we have that

$$\begin{aligned}\mathbb{E}[Y_t] &= \mathbb{E}[\alpha + U_t + \theta_1 U_{t-1}] \\ &= \alpha + \mathbb{E}[U_t] + \theta_1 \mathbb{E}[U_{t-1}] \\ &= \alpha.\end{aligned}$$

For the variance,

$$\begin{aligned}\gamma_0 &= \text{var}(Y_t) = \text{var}(\alpha + U_t + \theta_1 U_{t-1}) \\ &= \text{var}(U_t + \theta_1 U_{t-1}) \\ &= \text{var}(U_t) + \theta_1^2 \text{var}(U_{t-1}) + 2\theta_1 \text{cov}(U_t, U_{t-1}) \\ &= \sigma^2 + \theta_1^2 \sigma^2 + 0 \\ &= \sigma^2(1 + \theta_1^2).\end{aligned}$$

For the first autocovariance,

$$\begin{aligned}\gamma_1 &= \text{cov}(Y_t, Y_{t-1}) \\ &= \text{cov}(\alpha + U_t + \theta_1 U_{t-1}, \alpha + U_{t-1} + \theta_1 U_{t-2}) \\ &= \text{cov}(\theta_1 U_{t-1}, U_{t-1})\end{aligned}\tag{†}$$

because white noise is uncorrelated. Hence

$$\begin{aligned}\gamma_1 &= \theta_1 \text{cov}(U_{t-1}, U_{t-1}) \\ &= \theta_1 \text{var}(U_{t-1}) \\ &= \theta_1 \sigma^2.\end{aligned}$$

Higher order autocorrelations will be zero, because there will no common U_t terms in (†). Plugging these into the definition of the ACF, we have

$$\tau_1 = \frac{\gamma_1}{\gamma_0} = \frac{\theta_1 \sigma^2}{\sigma^2(1 + \theta_1^2)} = \frac{\theta_1}{1 + \theta_1^2}.$$

(e) **Optional:** The ACF is obtained by repeatedly substituting $Y_{t-i} = \phi_1 Y_{t-i-1} + \alpha + U_{t-i}$:

$$\begin{aligned}Y_t &= \phi_1 Y_{t-1} + \alpha + U_t \\ &= \phi_1^2 Y_{t-2} + \phi_1(\alpha + U_{t-1}) + \alpha + U_t \\ &= \phi_1^3 Y_{t-3} + \phi_1^2(\alpha + U_{t-2}) + \phi_1(\alpha + U_{t-1}) + \alpha + U_t \\ &\vdots \\ &= \phi_1^k Y_{t-k} + \sum_{i=0}^{k-1} \phi_1^i \alpha + \sum_{i=0}^{k-1} \phi_1^i U_{t-i}.\end{aligned}\tag{1}$$

Therefore,

$$\begin{aligned}\gamma_k &= \text{cov}(Y_t, Y_{t-k}) = \phi_1^k \text{cov}(Y_{t-k}, Y_{t-k}) + \sum_{i=0}^{k-1} \phi_1^i \text{cov}(U_{t-i}, Y_{t-k}) \\ &= \phi_1^k \text{var}(Y_{t-k}),\end{aligned}$$

so that

$$\tau_k = \frac{\gamma_k}{\gamma_0} = \phi_1^k.$$