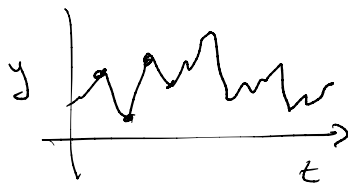


Temporal Models:

Suppose y_t for $t=1, \dots, T$ are observed over time:

To study dynamics of a time series:



First $z_t = y_t - \bar{y}$, then specify an autoregressive model:

$$z_t \sim N(\alpha z_{t-1}, \sigma^2), \quad t=2, \dots, T$$

If \underline{z} is stationary then $|\alpha| < 1$
 $\alpha \sim N(\mu_\alpha, \sigma_\alpha^2)$
 $\sigma^2 \sim \text{IG}(q, r)$

Posterior:

$$[\alpha, \sigma^2 | \underline{z}] \propto \left(\prod_{t=2}^T [z_t | z_{t-1}, \alpha, \sigma^2] \right) [\alpha] [\sigma^2]$$

Full-conditional distributions:

$$[\alpha | \cdot] \propto \left(\prod_{t=2}^T [z_t | z_{t-1}, \alpha, \sigma^2] \right) [\alpha]$$

$$\propto \exp \left\{ -\frac{1}{2} \sum_t \frac{(z_t - \alpha z_{t-1})^2}{\sigma^2} \right\} \exp \left\{ -\frac{1}{2} \frac{(\alpha - \mu_\alpha)^2}{\sigma_\alpha^2} \right\}$$

$$\propto \exp \left\{ -\frac{1}{2} \left(\underbrace{-2 \left(\sum_t \frac{z_t z_{t-1}}{\sigma^2} + \frac{\mu}{\sigma_\alpha^2} \right) \alpha}_{b} + \underbrace{\alpha^2 \left(\sum_t \frac{z_{t-1}^2}{\sigma^2} + \frac{1}{\sigma_\alpha^2} \right)}_a \right) \right\}$$

$$= N(a^{-1}b, a^{-1})$$

$$\begin{aligned}
 [\sigma^2 | \cdot] &\propto \left(\prod_{t=2}^T [z_t | z_{t-1}, \alpha, \sigma^2] \right) [\sigma^2] \\
 &\propto (\sigma^2)^{\frac{(T-1)}{2}} \exp \left\{ -\frac{1}{\sigma^2} \sum_t \frac{(z_t - \alpha z_{t-1})^2}{2} \right\} (\sigma^2)^{\frac{(q+1)}{2}} \exp \left\{ -\frac{1}{\sigma^2 r} \right\} \\
 &\propto (\sigma^2)^{\underbrace{\frac{(T-1)}{2} + \frac{(q+1)}{2}}_{\tilde{q}}} \exp \left\{ -\frac{1}{\sigma^2} \underbrace{\left(\sum_t \frac{(z_t - \alpha z_{t-1})^2}{2} + \frac{1}{r} \right)}_{\tilde{r}-1} \right\} \\
 &= \mathcal{IG}(\tilde{q}, \tilde{r})
 \end{aligned}$$

Bayesian forecasting: Use posterior pred. distrib (PPD)

$$\begin{aligned}
 [z_{T+1} | \underline{z}] &= \int \int [z_{T+1}, \alpha, \sigma^2 | \underline{z}] d\alpha d\sigma^2 \\
 &= \int \int \underbrace{[z_{T+1} | \alpha, \sigma^2, \underline{z}]}_{\text{pred. full cond.}} \underbrace{[\alpha, \sigma^2 | \underline{z}]}_{\text{posterior}} d\alpha d\sigma^2 \\
 &= \int \int [z_{T+1} | \alpha, \sigma^2, z_T] [\alpha, \sigma^2 | \underline{z}] d\alpha d\sigma^2
 \end{aligned}$$

Note: $[z_{T+1} | \alpha, \sigma^2, z_T] = N(z_T, \sigma^2)$

Procedure:

- 1.) Sample $\alpha^{(k)}, \sigma^{2(k)}$ using MCMC, $k=1, \dots, K$
- 2.) Sample $z_{T+1}^{(k)} \sim N(\alpha^{(k)} z_T, \sigma^{2(k)})$
for $k=1, \dots, K$

$$3.) \hat{z}_{T+1} = E(z_{T+1} | \underline{z}) = \frac{\sum_{k=1}^K z_{T+1}^{(k)}}{K}$$

"point forecast"