

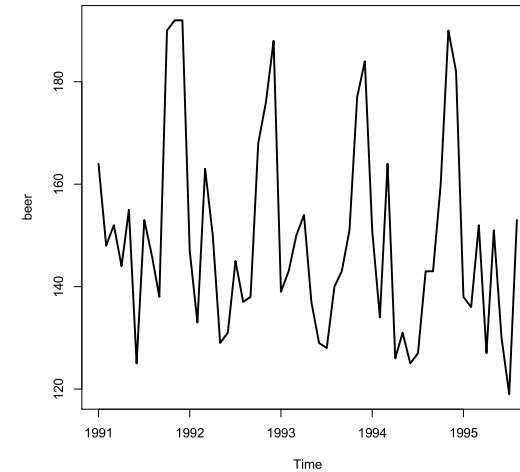
Time series analysis I

Example time series: Beer production. The Monthly Australian beer production has been observed between Jan 1991 to Aug 1995.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1991	164	148	152	144	155	125	153	146	138	190	192	192
1992	147	133	163	150	129	131	145	137	138	168	176	188
1993	139	143	150	154	137	129	128	140	143	151	177	184
1994	151	134	164	126	131	125	127	143	143	160	190	182
1995	138	136	152	127	151	130	119	153				

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Time series analysis II



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Time series analysis III

Questions:

- What are the patterns in the beer data ?
- What model can you propose to model this stochastic process ? (what explanatory variable would you use ?)

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ARIMA models I

Stochastic process s in the time domain

- AR(1)

$$\{s(t + \Delta) = c + \phi_1 s(t) + \epsilon(t + \Delta)\} \equiv \{s_{t+1} = c + \phi_1 s_t + \epsilon_{t+1}\}$$

- MA(1)

$$\{s(t + \Delta) = c + \phi_1 \epsilon(t) + \epsilon(t + \Delta)\} \equiv \{s_{t+1} = c + \phi_1 \epsilon_t + \epsilon_{t+1}\}$$

with Δ a fixed interval of time.


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ARIMA models II

Exercise: Assume a simple AR(1) model:

$$s_t = \alpha s_{t-1} + \epsilon_t \quad \text{with } \epsilon_t \sim \mathcal{N}(0, \sigma^2) \quad \forall t, |\alpha| < 1$$

with observations $\{s_t^{(1)}\}_{t=1, \dots, n}$. Draw a probabilistic graph to model this time series.

 Gaussian Markov Random Fields - Theory and Applications, H. Rue & L. Held, 2005 (chp. 1).

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ARIMA models IV

Exercise: Given a temporal stochastic process s with the following Markov property

$$p(s_t | s_{t-1}) = \mathcal{N}(s_t; \alpha s_{t-1}, \sigma^2) \quad \forall t$$

with observations $\{s_t^{(1)}\}_{t=1, \dots, n}$.

- Estimate s at a new time $n + 1$ with its confidence interval.
- Give an estimate for s at a new time $n + 2$ with its confidence interval.

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ARIMA models III

Exercise: Assume a simple AR(1) model:

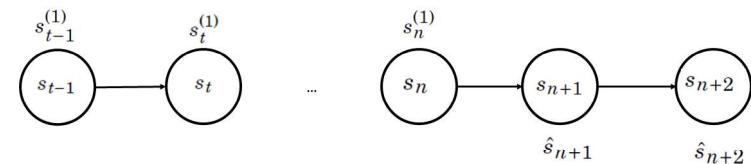
$$s_t = \alpha s_{t-1} + \epsilon_t \quad \text{with } \epsilon_t \sim \mathcal{N}(0, \sigma^2) \quad \forall t, |\alpha| < 1$$

Show

$$p(s_t | s_{t-1}, \dots, s_1) = p(s_t | s_{t-1}) = \mathcal{N}(s_t; \alpha s_{t-1}, \sigma^2)$$

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ARIMA models V



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ARIMA models VI

We know

$$p(s_t | s_{t-1}) = \mathcal{N}(s_t; \alpha s_{t-1}, \sigma^2) \quad \forall t$$

so at $n + 1$:

$$p(s_{n+1} | s_n) = \mathcal{N}(s_{n+1}; \alpha s_n, \sigma^2)$$

and we use the observation $s_n^{(1)}$ that is available for s_n :

$$p(s_{n+1} | s_n^{(1)}) = \mathcal{N}(s_{n+1}; \alpha s_n^{(1)}, \sigma^2)$$

A good estimate is the expectation $\hat{s}_{n+1} = \alpha s_n^{(1)}$ and the 95% prediction interval is $\hat{s}_{n+1} \pm 2\sigma$.

ARIMA models VII

At $n + 2$:

$$p(s_{n+2} | s_{n+1}) = \mathcal{N}(s_{n+2}; \alpha s_{n+1}, \sigma^2)$$

But we don't have observation for s_{n+1} ! so instead we use:

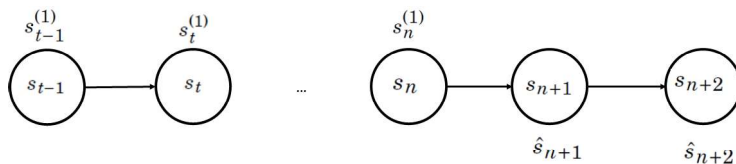
$$\begin{aligned} p(s_{n+2} | s_n) &= \int p(s_{n+2}, s_{n+1} | s_n) ds_{n+1} \\ &= \int p(s_{n+2} | s_{n+1}, s_n) p(s_{n+1} | s_n) ds_{n+1} \\ &= \int p(s_{n+2} | s_{n+1}) p(s_{n+1} | s_n) ds_{n+1} \\ &= \int \mathcal{N}(s_{n+2}; \alpha s_{n+1}, \sigma^2) \mathcal{N}(s_{n+1}; \alpha s_n, \sigma^2) ds_{n+1} \\ &= \mathcal{N}(s_{n+2}; \alpha^2 s_n, \sigma^2 (1 + \alpha^2)) \end{aligned}$$

A good estimate is the expectation $\hat{s}_{n+2} = \alpha^2 s_n^{(1)}$ using the observation $s_n^{(1)}$, and the 95% prediction interval is $\hat{s}_{n+2} \pm 2\sigma \sqrt{1 + \alpha^2}$.

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ARIMA models VIII



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