

Linear time series

- AR

- AR(1) without a drift: $r_t = \phi_1 r_{t-1} + a_t$

- another formula

$$\begin{aligned}
 r_t &= \phi_1 r_{t-1} + a_t \\
 r_{t-1} &= \phi_1 r_{t-2} + a_{t-1} \\
 &\vdots \\
 r_1 &= \phi_1 r_0 + a_1
 \end{aligned}
 \quad \left. \begin{aligned}
 r_t &= \phi_1(\phi_1 r_{t-2} + a_{t-1}) + a_t = \phi_1^2 r_{t-2} + \phi_1 a_{t-1} + a_t \\
 &= \phi_1^2 (\phi_1 r_{t-3} + a_{t-2}) + \phi_1 a_{t-1} + a_t \\
 &= \phi_1^3 r_{t-3} + \phi_1^2 a_{t-2} + \phi_1 a_{t-1} + a_t \\
 &= \phi_1^t r_0 + \phi_1^{t-1} a_1 + \dots + \phi_1 a_{t-1} + a_t
 \end{aligned} \right\}$$

我们可以一直循环
 We can let $r_0 = 0$. $\Leftrightarrow |\phi_1| < 1$. So a_t 越大， r_t 的绝对值越小。

$$\Rightarrow r_t = \sum_{i=0}^t \phi_1^i a_{t-i}$$

- stationary: if $|\phi_1| >= 1 \rightarrow r_t$ 不收敛

- $|\phi_1| < 1$ mean reverting behavior: 什么意义? 当t-1时的收益小于0时, 收益率的变化率的期望大于0, 也就是说很有可能收益率会上升, 也就是回归0均值, 反之

$$\begin{aligned}
 |\phi_1| < 1 \rightarrow & |\phi_1| < 1 \quad \Delta r_t = r_t - r_{t-1} \quad r_t = \phi_1 r_{t-1} + a_t \\
 E[\Delta r_t | F_{t-1}] &= E[\underbrace{(\phi_1 - 1)r_{t-1}}_{< 0} + a_t | F_{t-1}] < 0 \quad \text{if } r_{t-1} > 0 \\
 &E[\Delta r_t | F_{t-1}] > 0 \quad \text{if } r_{t-1} < 0
 \end{aligned}$$

- $|\phi_1| = 1$ random walk
- $|\phi_1| > 1$ infinity, explosive process
- $E[r_t] = 0$
- $Var(r_t) = \frac{\sigma_a^2}{1-\phi_1^2}$
- ACF 指数递减

$$\begin{aligned}
 E[r_t] &= E\left[\sum_{i=0}^{\infty} \phi_1^i a_{t-i}\right] = 0 \\
 Var(r_t) &= \sum_{i=0}^{\infty} \phi_1^{2i} Var(a_{t-i}) = \sum_{i=0}^{\infty} \phi_1^{2i} \sigma_a^2 = \sigma_a^2 \cdot \frac{1}{1-\phi_1^2} = \frac{\sigma_a^2}{1-\phi_1^2} \\
 r_k &= E[r_t r_{t+k}] = E\left[\left(\sum_{i=0}^{\infty} \phi_1^i a_{t-i}\right) \left(\sum_{j=0}^{\infty} \phi_1^j a_{t+k-j}\right)\right] \\
 &= E\left[\left(\underbrace{a_t + \phi_1 a_{t-1} + \phi_1^2 a_{t-2} + \dots + \phi_1^k a_{t-k} + \phi_1^{k+1} a_{t-k+1} + \dots}\right) \right. \\
 &\quad \left. \left(\underbrace{a_{t+k} + \phi_1 a_{t+k-1} + \dots}\right)\right] \\
 &= (\phi_1^k + \phi_1^{k+1} + \dots) \sigma_a^2 \\
 \Rightarrow r_k &= \frac{\phi_1^k}{1-\phi_1^2} \sigma_a^2 / \frac{\sigma_a^2}{1-\phi_1^2} = \phi_1^k \Rightarrow \text{ACF 指数递减}
 \end{aligned}$$

- AR(1) with a drift: $r_t = \phi_1 r_{t-1} + a_t + \phi_0$

- properties

$$\begin{aligned}
r_t &= \phi_0 + \phi_1 r_{t-1} + a_t \\
&= \phi_0 + \phi_1 (\phi_0 + \phi_1 r_{t-2} + a_{t-1}) + a_t \\
&= \phi_0 + \phi_0 \phi_1 + \phi_1^2 r_{t-2} + \phi_1 a_{t-1} + a_t \\
&= \phi_0 + \phi_0 \phi_1 + \phi_1^2 (\phi_0 + \phi_1 r_{t-3} + a_{t-2}) + \phi_1 a_{t-1} + a_t \\
&\quad \vdots \\
&= \phi_0 - \frac{1}{1-\phi_1} + \sum_{i=0}^{\infty} \phi_1^i a_{t-i} \\
\Rightarrow E[r_t] &= \frac{\phi_0}{1-\phi_1} \\
Var(r_t) &= \frac{\phi_0}{1-\phi_1} + \sum_{i=0}^{\infty} \phi_1^{2i} \sigma_a^2 = \underbrace{\frac{\phi_0}{1-\phi_1}}_{\text{also not changed}} + \underbrace{\frac{\sigma_a^2}{1-\phi_1^2}}_{\text{also not changed}} \\
r_k &= E[(r_t - \frac{\phi_0}{1-\phi_1})(r_{t+k} - \frac{\phi_0}{1-\phi_1})] \Rightarrow \text{not changed.}
\end{aligned}$$

- forecast

- 1-2 step

$$\begin{aligned}
\hat{r}_{n+1} &= E[r_{n+1} | r_n] = E[\phi_0 + \phi_1 r_n + a_{n+1} | r_n] \\
&= \phi_0 + \phi_1 r_n \\
e_{n+1} &= r_{n+1} - \hat{r}_{n+1} = \phi_0 + \phi_1 r_n + a_{n+1} - \phi_0 - \phi_1 r_n = a_{n+1} \\
Var(e_{n+1}) &= Var(a_{n+1}) = \sigma_a^2 \\
\hat{r}_{n+2} &= E[r_{n+2} | r_n] = E[\phi_0 + \phi_1 (\phi_0 + \phi_1 r_n + a_{n+1}) + a_{n+2} | r_n] \\
&= \phi_0 + \phi_1 \phi_0 + \phi_1^2 r_n \\
e_{n+2} &= r_{n+2} - \hat{r}_{n+2} = \phi_1 a_{n+1} + a_{n+2} \\
Var(e_{n+2}) &= (\phi_1^2 + 1) \sigma_a^2 \Rightarrow Var(e_{n+1}) \Rightarrow \text{step } \uparrow \text{ uncertainty } \uparrow
\end{aligned}$$

- 1 step

$$\begin{aligned}
\hat{Y}_{n+l} &= E[Y_{n+l} | Y_n] = E[\phi_0 + \phi_1 Y_{n+l-1} + a_{n+l} | Y_n] \\
&= \phi_0 + \phi_1 \hat{Y}_{n+l-1} \\
&= \phi_0 + \phi_1 (\phi_0 + \phi_1 \hat{Y}_{n+l-2}) \\
&= \phi_0 + \phi_0 \phi_1 + \phi_1^2 (\phi_0 + \phi_1 \hat{Y}_{n+l-3}) \\
&= \phi_0 (1 + \phi_1 + \phi_1^2) + \phi_1^3 \hat{Y}_{n+l-3} \\
&\vdots \\
&= \phi_0 (1 + \phi_1 + \phi_1^2 + \dots + \phi_1^{l-1}) + \phi_1^{l-1} \hat{Y}_{n+l-1} \\
&= \phi_0 (1 + \phi_1 + \dots + \phi_1^{l-1}) + \phi_1^l Y_n
\end{aligned}$$

$$\begin{aligned}
Y_{n+l} &= \phi_0 + \phi_1 Y_{n+l-1} + a_{n+l} \\
&= \phi_0 + \phi_1 (\phi_0 + \phi_1 Y_{n+l-2} + a_{n+l-1}) + a_{n+l} \\
&= \phi_0 (1 + \phi_1) + \phi_1^2 Y_{n+l-2} + \phi_1 a_{n+l-1} + a_{n+l} \\
&= \phi_0 (1 + \phi_1 + \phi_1^2) + \phi_1^3 Y_{n+l-3} + \phi_1^2 a_{n+l-2} + \phi_1 a_{n+l-1} + a_{n+l} \\
&\vdots \\
&= \phi_0 (1 + \phi_1 + \dots + \phi_1^{l-1}) + \phi_1^l Y_n + \phi_1^{l-1} a_{n+l-1} + \dots + a_{n+l} \\
\Rightarrow \hat{Y}_{n+l} &= \phi_1^{l-1} a_{n+l-1} + \dots + a_{n+l} = \sum_{i=0}^{l-1} \phi_1^i a_{n+l-i} \\
\text{Var}(\hat{Y}_{n+l}) &= (\phi_1^{2(l-1)} + \dots + 1) 6a = \frac{1 - \phi_1^{2l}}{1 - \phi_1^2} 6a = 6a \sum_{i=0}^{l-1} \phi_1^{2i}
\end{aligned}$$

- Forcast interval

$$\begin{aligned}
Y_{n+l} &= \hat{Y}_{n+l} + \hat{\epsilon}_{n+l} \in [\phi_1^{l-1} a_{n+l-1} + \dots + a_{n+l}] \\
&\quad \mu \quad \text{Var. 也不应该是常数?} \\
&\quad \text{但不是 normal? 难道是因为 } n \rightarrow \infty, S_0 \xrightarrow{P} N(0, 6a) \\
\Rightarrow Y_{n+l} | F_n &\sim N(\hat{Y}_{n+l}, \sqrt{6a \sum_{i=0}^{l-1} \phi_1^{2i}}) \quad Y_n \text{ 此时是 constant} \\
\Rightarrow F_1 &\left(\hat{Y}_{n+l} - N \frac{1}{\sqrt{6a}} \sqrt{\sum_{i=0}^{l-1} \phi_1^{2i}}, \hat{Y}_{n+l} + N \frac{1}{\sqrt{6a}} \sqrt{\sum_{i=0}^{l-1} \phi_1^{2i}} \right)
\end{aligned}$$

- compact form

$$\begin{aligned}
Y_t &= \phi_0 + \phi_1 Y_{t-1} + a_t \\
&= \phi_0 + \phi_1 B r_t + a_t \\
(-\phi_1 B) Y_t &= \phi_0 + a_t
\end{aligned}$$

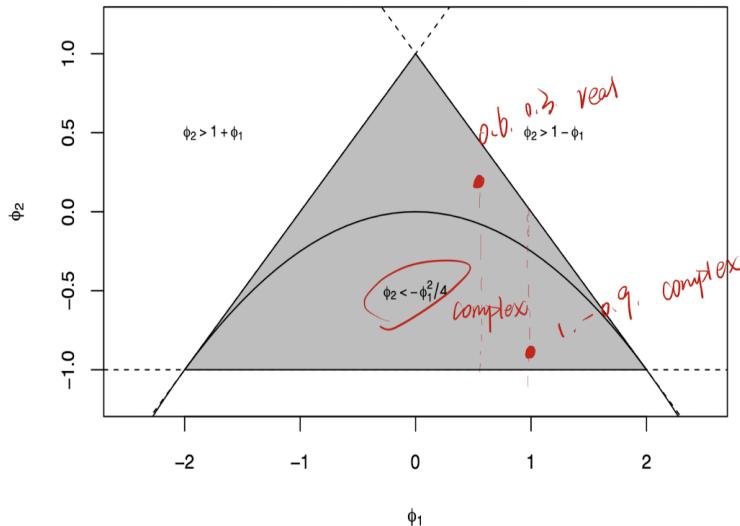
- AR(2) without a drift: $r_t = \phi_1 r_{t-1} + \phi_2 r_{t-2} + a_t$
 - stationary condition

$$\begin{aligned}
Y_t &= \phi_0 + \phi_1 Y_{t-1} + a_t \\
&= \phi_0 + \phi_1 B Y_t + a_t \\
(-\phi_1 B) Y_t &= \phi_0 + a_t \\
Y_t &= \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + a_t \\
&= \phi_1 B Y_t + \phi_2 B^2 Y_t + a_t \\
(1 - \phi_1 B - \phi_2 B^2) Y_t &= a_t \\
&\stackrel{\text{=0的解在单位圆之外}}{=} \\
&= (1 - \alpha_1 z)(1 - \alpha_2 z) \quad z_1 = \frac{1}{\alpha_1}, z_2 = \frac{1}{\alpha_2} > 1 \Leftrightarrow (|\alpha_1| < 1, |\alpha_2| < 1) \\
&\Rightarrow (1 - 2z)(1 - \alpha_2 z) Y_t = a_t \\
\text{we let } u_t &= (1 - \alpha_2 z) Y_t \\
(1 - \alpha_1 z) u_t &= a_t \quad u_t = \sum_{i=0}^{\infty} \alpha_1^i a_{t-i} \quad |\alpha_1| < 1 \\
u_t &= \alpha_2 Y_{t-1} + u_{t-1} = \sum_{i=0}^{\infty} \alpha_2^i u_{t-i} \quad |\alpha_2| < 1 \Rightarrow \text{stationary}
\end{aligned}$$

Stationarity condition is equivalent to

$$\begin{cases} \phi_2 + \phi_1 < 1, \\ \phi_2 - \phi_1 < 1, \\ -1 < \phi_2 < 1. \end{cases}$$

- but some special cases



- if in the triangle but not in the semi-circle: two real roots
- if in the semi-circle but not in the triangle: two complex roots
- 不可能一个实根一个虚数根, 边界值not station, outside the triangle--> explosive

- ACF

$$\Rightarrow Y_t = \sum_{i=0}^{\infty} \phi_i Y_{t-i} = \sum_{i=0}^{\infty} \phi_i \left(\sum_{j=0}^{\infty} \phi_j a_{t-i-j} \right)$$

$$E[Y_t] = 0$$

$$r_1 = E[Y_t Y_{t+1}] = E[(\phi_1 Y_{t-1} + \phi_2 Y_{t-2} + a_t) Y_{t+1}]$$

$$= E[\phi_1^2 Y_{t-1}^2 + \underbrace{\phi_1 \phi_2 Y_{t-2} Y_{t-1}}_{a_t Y_{t-1}} + a_t Y_{t+1}]$$

$$= \phi_1 r_0 + \phi_2 r_1$$

$$r_1 = \frac{\phi_1 r_0}{1 - \phi_2} \quad p_1 = \frac{\phi_1}{1 - \phi_2}$$

$$r_k = E[Y_t Y_{t+k}] = E[(\phi_1 Y_{t-1} + \phi_2 Y_{t-2} + a_t) Y_{t+k}]$$

$$= \phi_1 r_{k-1} + \phi_2 r_{k-2}$$

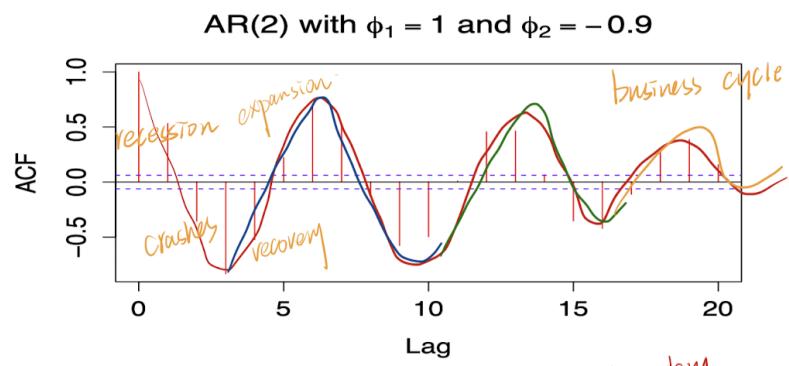
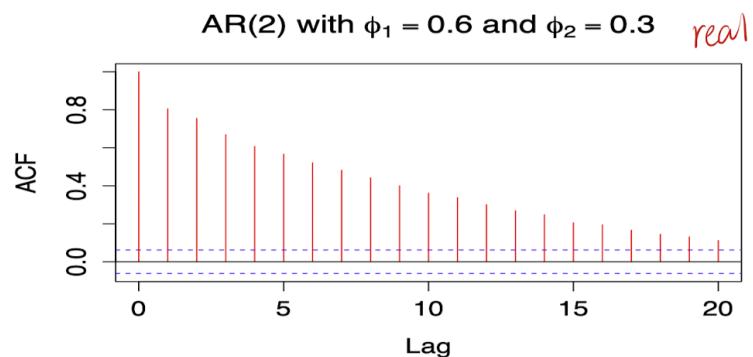
$$p_k = \phi_1 p_{k-1} + \phi_2 p_{k-2}$$

- ω_1, ω_2 是系数方程式的、两个解

- if two real solutions

$$\rho_l = \frac{c_1}{\omega_1^l} + \frac{c_2}{\omega_2^l},$$

- if two complex solutions, forming sine and cosine waves



- 根据上述的图-->business cycle <-two complex solutions
 - average length

$$k = \frac{2\pi}{\cos^{-1}[\phi_1/(2\sqrt{-\phi_2})]}$$

- forecast

- E

$$E[r_t] = \phi_0 + \phi_1 E[r_{t-1}] + \phi_2 E[r_{t-2}]$$

$$E = \frac{\phi_0}{1 - \phi_1 - \phi_2}$$

- AR(p)

$$r_t = \phi_0 + \phi_1 r_{t-1} + \phi_2 r_{t-2} + \cdots + \phi_p r_{t-p} + a_t$$

- stationary : roots all are outside the unit circle
- order specification:
 - ACF 递减
 - PACF 找不等于0的点, ϕ_{kk}

$$\begin{aligned} & \text{Corr}(r_t, r_{t+k} | r_{t+1}, \dots, r_{t+k-1}) \\ &= \frac{\text{Cov}[(r_t - \hat{r}_t)(r_{t+k} - \hat{r}_{t+k})]}{\sqrt{\text{Var}(r_t - \hat{r}_t)\text{Var}(r_{t+k} - \hat{r}_{t+k})}} \end{aligned}$$

Formula: $\phi_{11} = \rho_1$,

$$\phi_{kk} = \frac{\left| \begin{array}{cccccc} 1 & \rho_1 & \rho_2 & \cdots & \rho_{k-2} & \rho_1 \\ \rho_1 & 1 & \rho_1 & \cdots & \rho_{k-3} & \rho_2 \\ & & \cdots & & & \\ & & & & & \\ \rho_{k-1} & \rho_{k-2} & \rho_{k-3} & \cdots & \rho_1 & \rho_k \\ \hline 1 & \rho_1 & \rho_2 & \cdots & \rho_{k-2} & \rho_{k-1} \\ \rho_1 & 1 & \rho_1 & \cdots & \rho_{k-3} & \rho_{k-2} \\ & & \cdots & & & \\ & & & & & \\ \rho_{k-1} & \rho_{k-2} & \rho_{k-3} & \cdots & \rho_1 & 1 \end{array} \right|}{\left| \begin{array}{cccccc} 1 & \rho_1 & \rho_2 & \cdots & \rho_{k-2} & \rho_{k-1} \\ \rho_1 & 1 & \rho_1 & \cdots & \rho_{k-3} & \rho_{k-2} \\ & & \cdots & & & \\ & & & & & \\ \rho_{k-1} & \rho_{k-2} & \rho_{k-3} & \cdots & \rho_1 & 1 \end{array} \right|}$$

- sample PACF $\rightarrow \rho$ 不是真实的, 而是估计出来的

$$\hat{\phi}_{kk} = \frac{\begin{vmatrix} 1 & \hat{\rho}_1 & \hat{\rho}_2 & \cdots & \hat{\rho}_{k-2} & \hat{\rho}_1 \\ \hat{\rho}_1 & 1 & \hat{\rho}_1 & \cdots & \hat{\rho}_{k-3} & \hat{\rho}_2 \\ \vdots & & \vdots & & & \\ \hat{\rho}_{k-1} & \hat{\rho}_{k-2} & \hat{\rho}_{k-3} & \cdots & \hat{\rho}_1 & \hat{\rho}_k \end{vmatrix}}{\begin{vmatrix} 1 & \hat{\rho}_1 & \hat{\rho}_2 & \cdots & \hat{\rho}_{k-2} & \hat{\rho}_{k-1} \\ \hat{\rho}_1 & 1 & \hat{\rho}_1 & \cdots & \hat{\rho}_{k-3} & \hat{\rho}_{k-2} \\ \vdots & & \vdots & & & \\ \hat{\rho}_{k-1} & \hat{\rho}_{k-2} & \hat{\rho}_{k-3} & \cdots & \hat{\rho}_1 & 1 \end{vmatrix}}$$

- when $k>p$ 时, $\phi_{kk} = 0$

$$j>p, \rho_j = \frac{\text{cov}(r_t, r_{t-j})}{r_0} = \frac{E[(r_t - \mu)(r_{t-j} - \mu)]}{r_0}$$

r_t 和 r_{t-j} 中没有相同项 $\Rightarrow \rho_j = 0 \Rightarrow \hat{\phi}_{jj} \approx 0$.

$\hat{\phi}_{jj}$ 是 estimate. \rightarrow 不要是 0, 但 ≈ 0 .

$\hat{\phi}_{kk} \sim N(0, \frac{1}{n})$ n is number of data.

- estimation

- residuals

true: $r_t = \phi_{00} + \phi_{01}r_{t-1} + \phi_{02}r_{t-2} + \dots + \phi_{0p}r_{t-p} + a_t$ $\tilde{\phi}_0 = (\phi_{00}, \phi_{01}, \dots, \phi_{0p})'$
estimate: $r_t = \phi_0 + \phi_1r_{t-1} + \phi_2r_{t-2} + \dots + \phi_pr_{t-p} + a_t$ $\phi = (\phi_0, \phi_1, \dots, \phi_p)'$

$$a_t(\phi) = r_t - \phi_0 - \phi_1r_{t-1} - \dots - \phi_pr_{t-p}$$

$$a_t(\phi) = a_t \Leftrightarrow \phi = \hat{\phi}_0$$

$a_t(\phi)$ is residuals

- how to get a best estimator? 判断 ϕ 是否等于 ϕ_0

$$\min \sum \text{residual}^2 \quad S_k(\phi) = \sum_{t=1}^n a_t^2(\phi)$$

derivative

$$S'_k(\phi) = \sum_{t=1}^n 2a_t(\phi) \frac{\partial a_t(\phi)}{\partial \phi}$$

$$= \sum_{t=1}^n 2(r_t - \tilde{z}'_{t-1}\phi)(-\tilde{z}'_{t-1})$$

$$= -2 \sum_{t=1}^n r_t \tilde{z}'_{t-1} + 2 \sum_{t=1}^n \tilde{z}'_{t-1}^2 \phi = 0$$

derivative

$$\phi = \left(\sum_{t=1}^n r_t \tilde{z}'_{t-1} \right) \cdot \left(\sum_{t=1}^n \tilde{z}'_{t-1}^2 \right)^{-1} \text{best } \phi$$

$$S''_k(\phi) = 2 \sum_{t=1}^n \tilde{z}'_{t-1}^2 \geq 0$$

$$\Rightarrow \hat{\sigma}^2 = \frac{1}{n} \sum_{t=1}^n a_t(\hat{\phi})^2 \text{ 是否大于 } 0? \Rightarrow \text{hypothesis}$$

how to prove. ϕ & $\hat{\phi}_0$ is close? \Rightarrow hypothesis.

$$\sqrt{n}(\hat{\phi}_i - \phi_{0i}) \sim N(0, \hat{\sigma}^2) \quad \sqrt{n}(\hat{\phi}_i - \phi_{0i}) \sim N(0, \hat{\sigma}^2) \quad \hat{\sigma}^2 = \left(\sum_{t=1}^n \tilde{z}'_{t-1}^2 \right)^{-1} \hat{\sigma}^2$$

- model checking 判断 residuals 是否约等于0
 - acf of residuals =0
 - Box test: 和前面其实异曲同工, 这不是判断所有的residuals是否都等于0, 这里要p足够大, 才能认为 H_0 正确, 也就是residuals都等于0, g是number of parameters

$$Q(m) = T(T+2) \sum_{k=1}^m \frac{\hat{\rho}_k^2}{T-k} \sim \chi_{m-g}^2,$$

- model selection: 很多model其实应该都正确, 怎么比较模型之间的好坏呢?
 - AIC

$$AIC(l) = \ln(\hat{\sigma}_l^2) + \frac{2l}{T},$$

- BIC

$$BIC(l) = \ln(\hat{\sigma}_l^2) + \frac{l \ln(T)}{T}.$$

- MA

- MA(1)
 - $r_t = \mu + a_t - \theta a_{t-1}$
 - always stationary
 - properties

$$\begin{aligned} E[r_t] &= \mu, \quad \text{Var}(r_t) = \mu + (1+\theta^2)\sigma_a^2. \\ r_1 &= \text{cov}(r_t, r_{t-1}) = E[(r_t - \mu)(r_{t-1} - \mu)] \\ &= E[(a_t - \theta a_{t-1})(a_{t-1} - \theta a_{t-2})] \\ &= -\theta \sigma_a^2 \quad r_{t-1} = \mu. \\ r_2 &= E[(a_t - \theta a_{t-1})(a_{t-2} - \theta a_{t-3})] = 0. \\ r_k &= 0, \quad k > 1 \\ \Rightarrow \text{ACF} &\text{是} \text{slim dependence}. \text{ 现在 ACF} = 0 \\ \Rightarrow r_t &\text{与 } r_{t-1}, r_{t-2}, \dots \text{无关.} \end{aligned}$$

- 有讲过PACF的公式吗
- forecast

$$r_t = \mu + a_t - \theta a_{t-1}$$

$$\hat{r}_n(l) = E[r_{n+l} | F_n] = E[\mu + a_{n+l} - \theta a_n | F_n] \\ = \mu - \theta a_n$$

$$e_n(l) = r_{n+l} - \hat{r}_n(l) = \mu + a_{n+l} - \theta a_n - \mu + \theta a_n = a_{n+l}$$

$$\hat{e}_n(l) = E[r_{n+l} | F_n] = E[\mu + a_{n+l} - \theta a_{n+l-1} | F_n] \\ = \underbrace{\mu}_{a_{n+l} - \mu} \quad \text{MA only has previous time's value}$$

$$\text{Var}(\hat{e}_n(l)) = \begin{cases} 6\sigma^2 & l=1 \\ (1+\theta^2)6\sigma^2 & l>1 \end{cases}$$

- invertibility: the dependence of r_t on $r_{t-l} \rightarrow 0$ when l increases, $|\theta| < 1$
 - get a_t easily
 - dual property

$$r_n = \mu + a_n - \theta a_{n-1} \quad a_n = r_n + \theta a_{n-1} - \mu$$

$$a_{n-1} = r_{n-1} + \theta a_{n-2} - \mu$$

⋮

$$a_2 = r_2 + \theta a_1 - \mu$$

$$\begin{aligned} \text{MA}(1) \Rightarrow a_n &= r_n - \mu + \theta(r_{n-1} - \mu + \theta a_{n-2}) \\ &= (r_n - \mu) + \theta(r_{n-1} - \mu) + \theta^2(r_{n-2} - \mu + \theta a_{n-3}) \\ &= \dots \\ &= \sum_{i=0}^n (r_{n-i} - \mu) \theta^i + \theta^n a_0 \quad \text{when } |\theta| < 1, \text{ so can neglect} \\ &= \sum_{i=1}^n (r_{n-i} - \mu) \theta^i + r_t - \mu \Rightarrow \sum_{i=1}^n (r_{n-i} - \mu) \theta^i + r_t - \mu \end{aligned}$$

$$\begin{aligned} \text{AR}(\infty) \Rightarrow r_n &= a_n + \mu - \sum_{i=1}^{\infty} (r_{n-i} - \mu) \theta^i \\ &= \sum_{i=1}^{\infty} r_{n-i} + a_n + \frac{\mu}{1-\theta} \Rightarrow \text{dual property.} \end{aligned}$$

- MA(2)

- $r_t = \mu + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2}$
- properties

2. $E[Y_t] = \mu$. $\text{Var}(Y_t) = (1 + \theta_1^2 + \theta_2^2)\sigma^2$

3. Invertibility. $r_t = \mu + (1 - \theta_1 - \theta_2)at$. \Rightarrow Solutions outside the unit circle
 $= \mu + (1 - 2\theta_1)(1 - \theta_2)at$
 $\quad \quad \quad at$
 $ut = \theta_1 ut_{t-1} + r_{t-1} - \mu$. $AR(1) \Rightarrow |\theta_1| < 1$
 $at = \theta_2 at_{t-2} + ut$. $AR(1) \Rightarrow |\theta_2| < 1$.

4. $r_1 = E[(r_t - \mu)(r_{t-1} - \mu)] = E[(a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2})(a_{t-1} - \theta_1 a_{t-2} - \theta_2 a_{t-3})]$

$$P_1 = \frac{-\theta_2 \theta_1 (1 - \theta_2)}{\theta^2 (1 + \theta_1^2 + \theta_2^2)} = \frac{-\theta_1 (1 - \theta_2)}{1 + \theta_1^2 + \theta_2^2}$$

$$r_2 = E[(r_t - \mu)(r_{t-2} - \mu)] = E[(a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2})(a_{t-2} - \theta_1 a_{t-3} - \theta_2 a_{t-4})]$$

$$P_2 = \frac{-\theta_2 \theta_1^2}{\theta^2 (1 + \theta_1^2 + \theta_2^2)} = \frac{-\theta_2}{1 + \theta_1^2 + \theta_2^2}$$

$$\beta_3 = 0, \beta_2 = 0$$

\Rightarrow always stationary

5. forecast

$$\hat{r}_{n+1} = E[r_{n+1} | F_n] = E[\mu + a_{n+1} - \theta_1 a_n - \theta_2 a_{n-1} | F_n]$$

$$= \mu - \theta_1 a_n - \theta_2 a_{n-1}$$

$$\hat{e}_n(1) = \mu + a_{n+1} - \theta_1 a_n - \theta_2 a_{n-1} + \theta_1 a_n + \theta_2 a_{n-1} = a_{n+1}$$

$$\hat{r}_n(2) = E[r_{n+2} | F_n] = E[\mu + a_{n+2} - \theta_1 a_{n+1} - \theta_2 a_n | F_n] = \mu - \theta_2 a_n$$

$$\hat{e}_n(2) = a_{n+2} - \theta_1 a_{n+1}$$

$$\hat{r}_n(3) = E[r_{n+3} | F_n] = E[\mu + a_{n+3} - \theta_1 a_{n+2} - \theta_2 a_{n+1} | F_n] = \mu$$

$$\hat{e}_n(3) = a_{n+3} - \theta_1 a_{n+2} - \theta_2 a_{n+1}$$

\Rightarrow go to mean after 2 periods.

- MA(q)

 - definition

$$r_t = \mu + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_q a_{t-q},$$

 - invertibility

all the roots of $\theta(z) = 1 - \theta_1 z - \theta_2 z^2 - \cdots - \theta_q z^q = 0$
lie outside the unit circle.

$|z| > 1$

 - building an MA model

 - order <- ACF

$$E = \mu$$

$$r_1 = E[(r_t - \mu)(r_{t-1} - \mu)]$$

$$= E[(a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_q a_{t-q})(a_{t-1} - \theta_1 a_{t-2} - \cdots - \theta_{q-1} a_{t-q})]$$

$$= -\theta_1 + \theta_1 \theta_2 + \cdots + \theta_q \theta_{q-1}$$

when $k = q+1$

$$r_{q+1} = E[(r_t - \mu)(r_{t-q-1} - \mu)]$$

$$= E[(a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_q a_{t-q})(a_{t-q-1} - \cdots)] = 0$$

\Rightarrow ACF 在 $q+1$ 之后 = 0

 - estimation

 - MA(1) with $|\theta_0| < 1$

 - 我们之前这里是利用求导，令一阶导等于0，求最大值，但这里很困难

\Rightarrow ACF 在 $q+1 \geq 1 = 0$

$$r_t = a_t - \theta_0 a_{t-1} \quad r_t^* = -\theta a_{t-1} \quad r_t = a_t(\theta) - \theta a_{t-1}$$

$$S_n(\theta) = \sum_{t=1}^n [r_t - (\theta a_{t-1})]^2 \text{ 对 } \theta \text{ 求导} = \sum_{t=1}^n a_t(\theta)^2$$

我们不知道 $a_t(\theta)$. $a_1(\theta) = r_1 + \theta \times 0$.
 $a_2(\theta) = r_2 + \theta a_1(\theta)$

$$a_t(\theta) = r_t + \theta a_{t-1}(\theta)$$

$$\frac{\partial S_n(\theta)}{\partial \theta} = \sum_{t=1}^n 2 \cdot a_t(\theta) \cdot \frac{\partial a_t(\theta)}{\partial \theta}$$

$$\frac{\partial^2 S_n(\theta)}{\partial \theta^2} = \sum_{t=1}^n 2 \left(\frac{\partial a_t(\theta)}{\partial \theta} \frac{\partial a_t(\theta)}{\partial \theta} + a_t(\theta) \frac{\partial^2 a_t(\theta)}{\partial \theta^2} \right) \text{ too complicated.}$$

\Rightarrow Iteration we want $\frac{\partial S_n(\theta)}{\partial \theta} = 0$ can't find θ .

$$\Rightarrow \text{find } \hat{\theta}_{0.1}(1,1) \quad \frac{\partial S_n(\theta)}{\partial \theta} = \frac{\partial S_n(\hat{\theta}_0^*)}{\partial \theta} (\hat{\theta} - \hat{\theta}_0) \quad f(x) = f(a) + f'(a)(x-a) \\ + f''(a)(x-a)^2 \dots$$

$$\hat{\theta} = \hat{\theta}_0 - \left[\frac{\partial^2 S_n(\hat{\theta}_0^*)}{\partial \theta^2} \right]^{-1} \frac{\partial S_n(\hat{\theta}_0)}{\partial \theta} \quad \text{有余项 最后项} \\ \text{can't find } \hat{\theta}_1^* \quad \hat{\theta}_1^* = \hat{\theta}_0 - \left[\frac{\partial^2 S_n(\hat{\theta}_0^*)}{\partial \theta^2} \right]^{-1} \frac{\partial S_n(\hat{\theta}_0)}{\partial \theta} \quad \hat{\theta} = \hat{\theta}_0 \\ f(x) = f(a) + f'(a)(x-a) \quad \text{在 } \hat{\theta}_0 \text{ 处展开}$$

$$\Rightarrow \hat{\theta}_0 \rightarrow \hat{\theta}_1^* \quad \hat{\theta}_1 = \hat{\theta}_0 - \left[\frac{\partial^2 S_n(\hat{\theta}_0^*)}{\partial \theta^2} \right]^{-1} \frac{\partial S_n(\hat{\theta}_0)}{\partial \theta} \quad \text{can't find } \hat{\theta}_1^*$$

$$\Rightarrow \hat{\theta}_1 \rightarrow \hat{\theta}_2^* \quad \hat{\theta}_2 = \hat{\theta}_1 - \left[\frac{\partial^2 S_n(\hat{\theta}_1^*)}{\partial \theta^2} \right]^{-1} \frac{\partial S_n(\hat{\theta}_1)}{\partial \theta} \quad \text{can't find } \hat{\theta}_2^*$$

$$\hat{\theta} = \hat{\theta}_m - \left[\frac{\partial^2 S_n(\hat{\theta}_m^*)}{\partial \theta^2} \right]^{-1} \frac{\partial S_n(\hat{\theta}_m)}{\partial \theta}$$

$$\hat{\theta}_{m-1} \rightarrow \hat{\theta}_n$$

- ϕ 是否 close to ϕ_0

Theory:

$$\hat{\theta} \approx \theta_0$$

$$MA(1) \frac{\partial a_t}{\partial \theta}$$

$$\sqrt{n}(\hat{\theta} - \theta_0) \stackrel{\text{true}}{\sim} N(0, \Omega).$$

$$\sqrt{n}(\hat{\theta}_i - \theta_{0i}) \sim N(0, \hat{\sigma}_{ii}). \quad \frac{\partial a_t}{\partial \theta}$$

where

Some variable may be useless

$$\Omega = \left(\sum_{t=1}^n \frac{\partial a_{t-1}(\hat{\theta})}{\partial \theta} \frac{\partial a_{t-1}(\hat{\theta})}{\partial \theta'} \right)^{-1} \hat{\sigma}_a^2$$

- Model check
 - box test of residuals \rightarrow residuals are white noise \rightarrow ACF = 0 (independent) \rightarrow p 足够大
- ARMA
 - ARMA(1,1):

$$(1 - \phi_1 B)r_t = \phi_0 + (1 - \theta B)a_t,$$

$$r_t = \phi_1 r_{t-1} + \phi_0 + a_t - \theta_1 a_{t-1}.$$

- stationary: same as AR
- invertibility: same as MA

Invertible: $a_t = \frac{r_t - \phi_0 - \phi_1 r_{t-1} + \theta_1 a_{t-1}}{W_t}$

$$a_t = \theta_1 a_{t-1} + W_t. \quad AR(1) \Rightarrow |\theta_1| < 1.$$

$$r_t = \phi_1 r_{t-1} + W_t + \phi_0. \quad AR(1) \Rightarrow |\phi_1| < 1.$$

- mean: $\frac{\phi_0}{1 - \phi_1}$

$$\begin{aligned} Y_1 &= E[(r_t - \mu)(r_{t-1} - \mu)] = E[(\phi_1 r_{t-1} + \phi_0 + a_t - \theta_1 a_{t-1})(r_{t-1} - \mu)] \\ &= \phi_1 E[r_{t-1}^2] - \theta_1 E[a_{t-1} r_{t-1}] \\ &\quad \left(E[a_{t-1} r_{t-1}] = E[a_{t-1}(\phi_1 r_{t-2} + a_{t-1} - \theta_1 a_{t-2})] \right) \\ &= \phi_1 r_0 - \theta_1 \sigma_a^2. \end{aligned}$$

$$\rho_1 = \phi_1 - \frac{\theta_1 \sigma_a^2}{r_0} \neq \phi_1.$$

$$\begin{aligned} r_2 &= E[r_t r_{t-2}] = E[(\phi_1 r_{t-1} + \phi_0 + a_t - \theta_1 a_{t-1}) r_{t-2}] \\ &= \phi_1 r_1 \\ \Rightarrow r_k &= \phi_1 r_{k-1} = \phi_1^{k-1} r_1. \quad \rho_k = \phi_1^{k-1} \rho_1. \quad ACF. \downarrow \end{aligned}$$

PACF. never equal to 0

- consider $\phi_0 = 0$
- forecast

$$\begin{aligned} \hat{r}_n(1) &= E[r_{n+1} | F_n] = E[\phi_1 r_n + \phi_0 + a_{n+1} - \theta_1 a_n | F_n] \\ &= \phi_1 r_n + \phi_0 - \theta_1 a_n. \end{aligned}$$

$$\hat{a}_n(1) = a_{n+1}$$

$$\begin{aligned} \hat{r}_n(2) &= E[r_{n+2} | F_n] = E[\phi_1 r_{n+1} + \phi_0 + a_{n+2} - \theta_1 a_{n+1} | F_n] \\ &= \phi_1 \hat{r}_n(1) + \phi_0. \end{aligned}$$

affect indirectly.

- ARMA(p,q)

- definition

$$\begin{aligned} r_t &= \phi_0 + \phi_1 r_{t-1} + \phi_2 r_{t-2} + \cdots + \phi_p r_{t-p} \\ &\quad + a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q}, \end{aligned}$$

- condition

where all the roots of

$$\phi_p(z) = 1 - \sum_{i=1}^p \phi_i z^i \text{ and } \theta_q(z) = 1 - \sum_{i=1}^q \theta_i z^i$$

lie outside the unit circle, and they have no common roots.

- representations

Representations:

$$\phi_p(z)\theta_q^{-1}(z) = 1 - \sum_{i=1}^{\infty} \pi_i z^i,$$

$\pi_i = O(\rho^i)$ with $\rho \in (0, 1)$. AR representation:

$$r_t = \theta_q^{-1}(1)\phi_0 + a_t + \pi_1 r_{t-1} + \pi_2 r_{t-2} + \dots$$

It tells how r_t depends on its past values. *at*

$$\phi_p^{-1}(z)\theta_q(z) = 1 + \sum_{i=1}^{\infty} \psi_i z^i,$$

$\psi_i = O(\rho^i)$ with $\rho \in (0, 1)$. MA representation:

$$r_t = \phi_0\phi_p^{-1}(1) + a_t + \psi_1 a_{t-1} + \psi_2 a_{t-2} + \dots$$

It tells how r_t depends on the past shocks. *at*

- FI

- 对 $e_n(l)$ 的估计

$$Y_{n+l} = \alpha_0 + \alpha_1 Y_{n+l-1} + \alpha_2 Y_{n+l-2} + \dots$$

$$E[Y_{n+l} | F_n] = \mu + \alpha_1 a_{n+l-1} + \alpha_2 a_{n+l-2} + \dots$$

$$\therefore E[e_n(l)] = a_{n+l} + \alpha_1 a_{n+l-1} + \alpha_2 a_{n+l-2} + \dots + \alpha_{l-1} a_{n+1}$$

$$\therefore \text{Var}[e_n(l)] = (1 + \alpha_1^2 + \alpha_2^2 + \dots)^2 \sigma_a^2$$

- confidence interval

$$\left[\hat{r}_n(l) - N_{\frac{\alpha}{2}} \sigma_a \sqrt{\sum_{j=0}^{l-1} \psi_j^2}, \hat{r}_n(l) + N_{\frac{\alpha}{2}} \sigma_a \sqrt{\sum_{j=0}^{l-1} \psi_j^2} \right]$$

- non-stationary time series

- 我们考虑 random walk: $p_t = p_{t-1} + a_t + \mu$

- properties:

- non-stationary:

$$\begin{aligned}
 P_t &= P_{t-1} + a_t + \mu \\
 &= a_t + \mu + \mu + a_{t-1} + P_{t-2} + \dots \\
 &= t\mu + P_0 + a_{t-1} + a_{t-2} + \dots \rightarrow \infty
 \end{aligned}$$

$$E[P_t] = \mu t + P_0. \quad \text{straight line}$$

- strong memory--ACF $\rightarrow 1$

$$\begin{aligned}
 E[Y_t | \mu=0] Y_{t+k} &= E[(Y_t - \mu)(Y_{t+k} - \mu)] \\
 &= E[(Y_t - P_0)(Y_{t+k} - P_0)] \\
 &= E[a_t + a_{t+1} + \dots + a_t](a_{t+k} + a_{t+k-1} + \dots + a_t) \\
 &= E[a_{t+k}^2 + a_{t+k-1}^2 + \dots + a_t^2] \\
 &= \frac{(t-k)\sigma_a^2}{t\sigma_a^2} \quad k=0 \text{ iff } \text{Var} = t\sigma_a^2 \\
 \rho_{tk} &= \sqrt{\frac{(t-k)\sigma_a^2}{t\sigma_a^2}} = \sqrt{1 - \frac{k}{t}} \rightarrow 1
 \end{aligned}$$

- have a time trend
- extension

$$\begin{aligned}
 P_t &= P_{t-1} - \theta a_{t-1} + a_t \\
 \text{Expansion: } a_t &= \underbrace{\theta a_{t-1}}_{(AR)} + (P_t - P_{t-1}) = \sum_{i=1}^{\infty} \theta^i (P_{t-i} - P_{t-1}). \\
 &= P_t + \theta P_{t-1} + \theta^2 P_{t-2} \dots \\
 &\quad - P_{t-1} - \theta P_{t-2} \dots \\
 &= P_t - (1-\theta)P_{t-1} - \theta(1-\theta)P_{t-2} \dots \\
 &= P_t - (1-\theta) \sum_{i=1}^{\infty} \theta^i P_{t-i}
 \end{aligned}$$

- how to test the unit root?
 - Dickey-Fuller test:

我们知道, 如果 $|\hat{\phi}_1| < 1 \Rightarrow \ln(\hat{\phi}_1 - 1) \sim N(0, \sigma^2)$ $\hat{\phi}_1 = \frac{\sum_{t=1}^n p_t p_{t+1}}{\sum_{t=1}^n p_t^2}$
 $H_0: \phi_1 = 1$ $H_a: \phi_1 \neq 1$ $\rho_n = \hat{\phi}_1 - 1 = \frac{\sum_{t=1}^n p_t p_{t+1}}{\sum_{t=1}^n p_t^2} - 1$
 $\ln(\hat{\phi}_1 - 1) \sim N(0, \sigma^2)$? 但这是不对的, 因为我们事先不知道 $|\phi_1| < 1$.

因此我们重新找一个方法估计 $\hat{\phi}_1$.
如果 $\phi_1 = 1 \Rightarrow p_t = e_t + e_{t-1} + \dots + e_1 + p_0 = \sum_{i=1}^t e_i$
 $P_{[n+1]} = \sum_{i=1}^n e_i$. random fun on $\mathcal{L}[e_i]$ $T_n = \sqrt{n}(\hat{\phi}_1 - 1) \sqrt{\sum_{t=1}^n p_{t+1}^2 / n^2}$
 $\frac{1}{\sqrt{n}} P_{[n+1]} = \frac{1}{\sqrt{n}} \sum_{i=1}^n e_i \rightarrow \mathcal{N}(0, \sigma^2)$ Brownian Motion.
 $\Rightarrow \sum_{t=1}^n P_{[t+1]} \Delta P_{[n+1]} \rightarrow \int_0^1 B(t) dB(t)$
 $\sum_{n=1}^{\infty} [\frac{1}{\sqrt{n}} P_{[n+1]}]^2 \rightarrow \int_0^1 B^2(t) dt$
 $P_n \xrightarrow{d} \frac{\int_0^1 B(t) dB(t)}{\int_0^1 B^2(t) dt}$
 $T_n \xrightarrow{d} \frac{\int_0^1 B(t) dB(t)}{\sqrt{\int_0^1 B^2(t) dt}}$ T_n \text{ 服从什么?}

- ARIMA:

- $\phi_p(B)(1-B)^d p_t = \theta_q(B)a_t$ $\phi_p(z) = 0, \theta_q(z) = 0$ 的解在单位圆外
- Var

$$\varphi(B) = \psi_p(B)(1-B)^d = 1 - \psi_p B - \psi_p B^2 - \dots - \psi_p B^{p-1}.$$

$$\varphi(B)p_t = \theta_q(B)a_t = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \dots - \theta_q a_{t-q}.$$

$$p_t = \psi_p p_{t-1} + \psi_p p_{t-2} + \dots + \psi_p p_{t-p}.$$

$\underbrace{a_t - \theta_1 a_{t-1} - \dots - \theta_q a_{t-q}}$.
error must be form by the unpredicted part. $\hat{a}_{t+1} = \sum_{j=0}^{t-1} \psi_j a_{t+j}$.

剩下的问题是如何计算 ψ_j .

$$\begin{aligned} p_{t+1} &= \sum_{j=1}^p \psi_j p_{t+1-j} + a_{t+1} = \sum_{j=1}^p \psi_j B^j p_{t+1} + a_{t+1} \\ &= p_{t+1} \sum_{j=1}^p \psi_j B^j + a_{t+1}. \\ p_{t+1} (1 - \sum_{j=1}^p \psi_j B^j) &= a_{t+1} \\ \therefore 1 - \sum_{j=1}^p \psi_j B^j &= \frac{a_{t+1}}{p_{t+1}} = \frac{\varphi_p(B)(1-B)^d}{\theta_q(B)} \\ \Rightarrow \psi_j &= \sum_{i=p}^{t-1} \psi_{j-i} \psi_i \end{aligned}$$
why?

- example

$$\text{example 1. } (1-B)P_t = (1-tB)A_t.$$

$$\frac{At}{Pt} = \frac{1-B}{1-tB} = (1-B)(1+tB + t^2B^2 + \dots)$$

$$= 1 + tB + t^2B^2 + \dots$$

$$-B - tB^2 - \dots$$

$$= 1 - (tB)B - \underbrace{t(1-t)}_{\vdots} B^2 - \dots$$

$$\therefore \bar{q}_j = (1-t)^{j-1}$$

$$q_0 = 1, \quad q_1 = \sum_{i=0}^{t-1} \bar{\pi}_{i+1} \bar{q}_i = \bar{\pi}_1 \bar{q}_1 = \bar{\pi}_1 = 1-t$$

$$q_2 = \sum_{i=0}^{t-1} \bar{\pi}_{i+2} \bar{q}_i = \bar{\pi}_2 \bar{q}_0 + \bar{\pi}_1 \bar{q}_1 = t(1-t) + (1-t)^2 = 1-t$$

$$q_3 = \sum_{i=0}^{t-1} \bar{\pi}_{i+3} \bar{q}_i = \bar{\pi}_3 \bar{q}_0 + \bar{\pi}_2 \bar{q}_1 + \bar{\pi}_1 \bar{q}_2$$

$$= t^2(1-t) + t(1-t)^2 + (1-t)^3$$

$$= t(1-t) + (1-t)^2 = (1-t)$$

\vdots

$$\text{So } q_j = \sum_{i=0}^{t-1} (1-t)^i A_{n+i-j} \quad \forall n \in \mathbb{N} : (1-t)^j t.$$

$$\cdot e_n(t) = \sum_{j=0}^{t-1} (1-t)^j A_{n+j} \quad \forall n \in \mathbb{N} : (1-t)^j t.$$