

Week 3: Sep. 26.

Lecture 4:

Trend estimation:

* Part I: model estimation

* Part II: smoothing (parametric)

* Part III: Isotonic regression (non-parametric)

Part I: Model Estimation

$$X_t = \underbrace{\mu_t}_{\text{Trend}} + \underbrace{e_t}_{\text{noise}}, \text{ assume } e_t \sim WN(0, \sigma^2), \text{ ACF of } \bar{X} \text{ is } \rho(h)$$

① Constant: $\mu_t = \mu$

$$\text{estimator: } \hat{\mu}_t \equiv \bar{X} = \frac{1}{n} \sum_{t=1}^n X_t \Rightarrow E(\hat{\mu}_t) = \mu \quad \text{Var}(\hat{\mu}_t) = \frac{\gamma(0)}{n} \left(1 + 2 \sum_{t=1}^{n-1} \left(1 - \frac{t}{n} \right) \rho(t) \right)$$

Remark: when X_t uncorrelated, $\text{Var}(\hat{\mu}_t) = \frac{\gamma(0)}{n}$

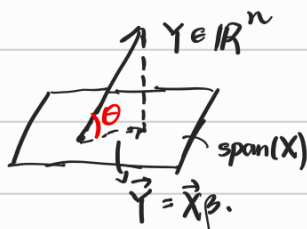
$$\begin{array}{c|cccc} t \backslash h & 1 & 2 & 3 & \dots & n-1 \\ \hline 1 & \gamma(1) & \gamma(2) & \dots & \dots & \gamma(n-1) \\ 2 & \gamma(1) & \gamma(2) & \dots & \dots & \gamma(n-1) \\ 3 & \vdots & \vdots & \gamma(2) & \dots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ n-1 & \gamma(1) & \gamma(2) & \dots & \dots & \gamma(n-1) \end{array}$$

$$\textcircled{2} \mu_t = \beta_0 + \beta_1 t \quad \text{or} \quad Y = X\beta + \varepsilon = \begin{pmatrix} \beta_1 \\ \beta_0 \end{pmatrix} \quad \begin{pmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_n \end{pmatrix}, \text{ where } \beta = \underset{\text{argmin}}{\text{argmin}} \|Y - X\beta\|^2$$

$$\hat{\beta} = (X^T X)^{-1} X^T Y$$

$$\hat{\beta}_1 = \frac{\sum_{t=1}^n (\mu_t - \bar{\mu})(t - \bar{t})}{\sum_{t=1}^n (t - \bar{t})^2}, \quad \bar{t} = \frac{n+1}{2}, \quad \hat{\beta}_0 = \bar{\mu} - \hat{\beta}_1 \bar{t}$$

Geometric Implementation of Least Square.



① $1 \in X$ (with intercept)

$$\frac{1}{n} \sum_{i=1}^n \hat{Y}_i = \frac{1}{n} \sum_{i=1}^n Y_i = \bar{Y}$$

$$e_i = Y_i - \hat{Y}_i : e \text{ residual}$$

$$e \perp X \ni 1 \rightarrow 1 \perp e \Rightarrow \langle e, 1 \rangle = 0 \Rightarrow \sum e_i = 0 \Rightarrow \sum \hat{Y}_i = \sum Y_i$$

Thus: $\frac{1}{n} \sum \hat{\mu}_i = \frac{1}{n} \sum \mu_i \Rightarrow$ unbiased

② evaluation

$\text{Cov}(\cdot, \cdot)$ 满足内积定义.

则 $\text{Var}(\cdot)$ 可理解为模长的平方

* $\text{Corr}(\hat{Y}, Y)$

* $\cos \theta$

* $R^2 = \frac{\text{Var}(\hat{Y})}{\text{Var}(Y)} = 1 - \frac{\text{Var}(Y - \hat{Y})}{\text{Var}(Y)} = \text{Corr}^2(\hat{Y}, Y) = \cos^2 \theta$

$\frac{\text{Cov}(\hat{Y}, Y)}{\sqrt{\text{Var}(\hat{Y})\text{Var}(Y)}}$

Exercise: Y, X_1, X_2

$Y \sim X_1 \Rightarrow R_1^2 = 0.1$

Q: $Y \sim X_1 \text{ and } X_2 \quad R^2 \in [?, ?]$

$Y \sim X_2 \Rightarrow R_2^2 = 0.2$

Solution:



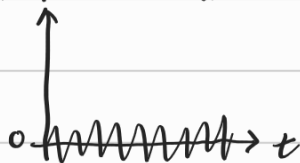
旋转 X_2 , X_1, X_2, Y 可共面. $\Rightarrow R^2 = 1$

ensemble $\rightarrow R^2 \uparrow$
 $\rightarrow \text{Var}(X_n) = \frac{1}{n} \text{Var}(X_i)$, 方差 \downarrow
 $\rightarrow \text{MSE} \downarrow = \text{var} + \text{bias}$.

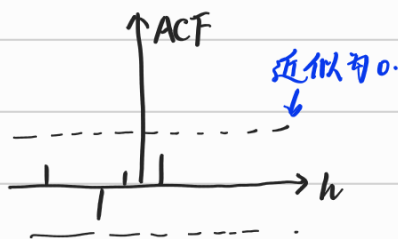
当 X_1 与 Y 的关系 (R^2) 确定, R^2 不会变得更好 $\Rightarrow R^2 = 0.2$.

* Evaluation \rightarrow Residual: $\hat{e}_t = X_t - \hat{\mu}_t$

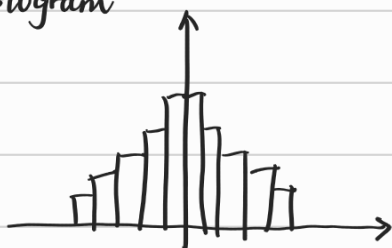
① residual plot:



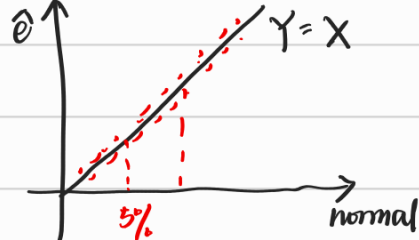
② ACF plot:



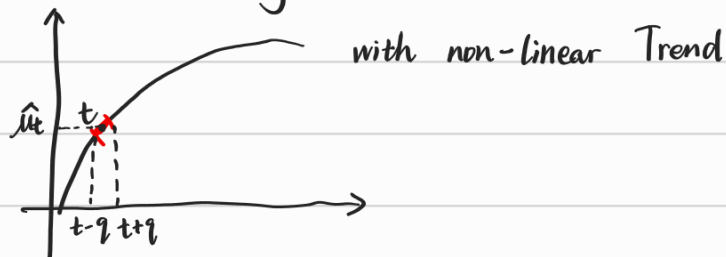
③ density plot / histogram



④ QQ-plot:



Part II: Smoothing



if linear.

$$\bar{\mu}_t = \frac{1}{2q+1} \sum_{h=-q}^q X_{t+h} = \frac{1}{2q+1} \sum_{h=-q}^q (X_{t+h} - \mu_{t+h} + \mu_{t+h}) = \frac{1}{2q+1} \sum_{h=-q}^q \mu_{t+h} + \frac{1}{2q+1} \sum_{h=-q}^q e_t$$

↑
t自己

Remark: ① $q \uparrow \Rightarrow e_t$ influence \downarrow , but might violate linearity

② end point issue.

③ smoothing \in linear filter - equal weight

$$\hat{\mu}_t = \sum_{h=-q}^q a_h X_{t+h}$$

- binomial
- exponential

Part III. isotonic regression

$$\min_{a_1, \dots, a_n} \sum_{t=1}^n (X_t - a_t)^2$$

s.t. a_1, \dots, a_n monotonic

① Pooled Adjacency: Violating Algo V.

No tuning parameters

No end-point issue.

when $q \uparrow$ $\left\{ \begin{array}{l} \text{bias} \uparrow \\ \text{variance} \downarrow \end{array} \right.$

Bias - Variance Trade-off

$$\text{MSE} = E(\hat{\mu} - \mu)^2 = \underbrace{(E(\hat{\mu}) - \mu)^2}_{\text{bias}} + \underbrace{E(\hat{\mu} - E(\hat{\mu}))^2}_{\text{variance}}$$

Assume noises are correlated

$$\text{Var}(\hat{\mu}_t) = \text{Var}(\bar{X}) = \text{Var}\left(\frac{1}{n} \sum_{t=1}^n X_t\right) = \frac{1}{n^2} \text{Var}\left(\sum_{t=1}^n X_t\right)$$

$$X_t = \mu_t + e_t, \quad e_t \sim WN(0, \sigma^2) \quad = \frac{1}{n^2} \left(\sum_{t=1}^n \text{Var}(X_t) + \right.$$

$$\rho(h) = \frac{\gamma(h)}{\gamma(0)} = \frac{\text{Cov}(X_t, X_{t+h})}{\text{Var}(X_t)}, \quad t \in \mathbb{Z}$$

$$\Rightarrow \gamma(h) = \rho(h) \gamma(0)$$

$$\text{Var}(X_1 + \dots + X_n)$$

$$= \text{Var}(X_1) + \text{Var}(X_2 + \dots + X_n) + 2 \text{Cov}(X_1, X_2 + \dots + X_n)$$

$$= \text{Var}(X_1) + \text{Var}(X_2 + \dots + X_n) + 2 \left[\rho(1) \gamma(0) + \rho(2) \gamma(0) + \dots + \rho(n-1) \gamma(0) \right]$$

$$= \text{Var}(X_1) + \text{Var}(X_2 + \dots + X_n) + 2 \gamma(0) [\rho(1) + \dots + \rho(n-1)]$$

$$= \sum_{t=1}^n \text{Var}(X_t) + 2 \gamma(0) \left[\begin{array}{c} \rho(1) + \dots + \rho(n-1) \\ \vdots \\ \rho(1) \end{array} \right] \quad \left. \vphantom{\sum_{t=1}^n} \right\} n-1$$

$$= n \cdot \gamma(0) + 2 \gamma(0) \cdot \sum_{h=1}^{n-1} (n-h) \rho(h)$$

$$\Rightarrow \frac{1}{n^2} \left[n \gamma(0) + 2 \gamma(0) \sum_{h=1}^{n-1} (n-h) \rho(h) \right]$$

$$\Rightarrow \frac{\gamma(0)}{n} \left[1 + 2 \sum_{h=1}^{n-1} \left(1 - \frac{h}{n}\right) \rho(h) \right]$$