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$$f(a) = E|X - a|$$

Предположим  $f_2(X, \lambda) = (X - \lambda)(\lambda - \mathbb{1}_{X < \lambda})$

$$f_2(X, \lambda) = \begin{cases} \lambda(X - \lambda) & X \geq \lambda \\ (\lambda - \lambda)(\lambda - X) & X < \lambda \end{cases}$$

Тогда  $L(a) = E[f_2(X, \lambda)] = \int_{-\infty}^{+\infty} [(x - a)dF(x) + (1 - \lambda)(a - \lambda)dF(x)]$

$$\frac{dL}{da} = - \int_a^{+\infty} dF(x) + (1 - \lambda) \int_{-\infty}^{\lambda} dF(x) = - \lambda(1 - F(a)) + (1 - \lambda)F(a) =$$

$$= -\lambda + \lambda F(a) + F(a) - \lambda F(a) = F(a) - \lambda \approx 0 \Rightarrow F(a) = \lambda$$

также  $a = q_{\lambda}$  — λ-квантиль не определена

$$\frac{d^2L}{da^2} = f(a) > 0 \Rightarrow L(a) = E[f_2(X, \lambda)]$$

максимизируется в  $a = q_{\lambda}$

№2

$$\mathbb{E}(Y_i | X_i) = \beta X_i, \quad \hat{\beta} = \frac{\sum Y_i X_i}{\sum X_i^2}$$

$$\hat{\beta} = \frac{\frac{1}{n} \sum Y_i X_i}{\frac{1}{n} \sum X_i^2} \quad \text{но } \mathbb{E}[X_i] \xrightarrow{\text{P}} \mathbb{E}[X_i^2] \xrightarrow{\text{P}} \mathbb{E}(Y_i | X_i)$$

$$\begin{aligned} \mathbb{E}(Y_i | X_i) &= \mathbb{E}[\mathbb{E}(Y_i | X_i) | X_i] = \mathbb{E}[X_i \cdot \mathbb{E}(Y_i | X_i)] = \\ &= \mathbb{E}[X_i \cdot \beta X_i] = \beta \mathbb{E}[X_i^2] \end{aligned}$$

Тогда  $\hat{\beta} \xrightarrow{\text{P}} \mathbb{E}[X_i^2] = \beta \Rightarrow$  оценка есть оценка  
независимо от  $\beta$

Нуля  $\varepsilon_i = Y_i - \beta X_i$  — ошибка регрессии,  $\mathbb{E}[\varepsilon_i | X_i] = 0$

$$\hat{\beta} - \beta = \frac{\sum Y_i X_i^2 - \beta \sum X_i^2}{\sum X_i^2} = \frac{\sum (Y_i - \beta X_i) X_i^2}{\sum X_i^2} = \frac{\sum \varepsilon_i X_i^2}{\sum X_i^2}$$

$$\sqrt{n}(\hat{\beta} - \beta) = \frac{\sqrt{\frac{1}{n} \sum \varepsilon_i X_i^2}}{\left(\frac{1}{n} \sum X_i^2\right)} \xrightarrow{\text{no SB4}} \mathbb{E}[X_i^2]$$

$$\frac{1}{n} \sum \varepsilon_i X_i^2 \rightarrow ? \quad \mathbb{E}[\varepsilon_i X_i^2 | X_i] = X_i^2 \mathbb{E}[\varepsilon_i | X_i] = 0$$

$$\mathbb{E}[\varepsilon_i X_i^2] = 0$$

$$\mathbb{D}(\varepsilon_i X_i^2) = \mathbb{E}[\varepsilon_i^2 X_i^4] - (\mathbb{E}[\varepsilon_i X_i^2])^2 = \mathbb{E}[\mathbb{E}[\varepsilon_i^2 | X_i] \cdot X_i^4]$$

$$\begin{aligned} \text{Если } \mathbb{E}[\varepsilon_i^2 | X_i] &= \mathbb{E}[\varepsilon_i^2 | X_i] = \mathbb{D}[Y_i | X_i] \Rightarrow \mathbb{D}[\varepsilon_i X_i^2] = \\ &= \sigma^2 \mathbb{E}[X_i^4] \end{aligned}$$

$$\text{и по Унит } \frac{1}{n} \sum \varepsilon_i X_i^2 \xrightarrow{\text{P}} \mathcal{N}(0, \mathbb{E}[\varepsilon_i^2 X_i^4])$$

$$\text{и по Гауссу: } \sqrt{n}(\hat{\beta} - \beta) \xrightarrow{\text{P}} \mathcal{N}\left(0, \frac{\mathbb{E}[\varepsilon_i^2 X_i^4]}{\mathbb{E}[X_i^2]^2}\right)$$

№3

$$\mathbb{E}(Y_i | X_i) = \alpha + \beta X_i, \quad Y'_i = X_i + \xi_i$$

$$Y_i = \bar{\alpha} + \hat{\beta} X'_i + \varepsilon_i$$

$$\hat{\beta}_{\text{min}} = \frac{\sum (Y_i - \bar{Y})(X'_i - \bar{X}')}{\sum (X'_i - \bar{X})^2}$$

Но  $\varepsilon_i = Y_i - \bar{\alpha} - \beta X_i$  — остаток в регрессии  $\Rightarrow \mathbb{E}(\varepsilon_i | X_i) = 0$   
значит  $\hat{\beta}_{\text{min}}$

$$\begin{aligned} \hat{\beta} &= \frac{1}{n} \sum (Y_i - \bar{Y})(X'_i - \bar{X}') = \frac{1}{n} \sum (\beta X_i + \varepsilon_i - \bar{\beta} \bar{X} - \bar{\varepsilon})(X_i + \xi_i - \bar{X} - \bar{\xi}) \\ &= \frac{1}{n} \sum (\beta(X_i - \bar{X}) + (\varepsilon_i - \bar{\varepsilon}))((X_i - \bar{X}) + (\xi_i - \bar{\xi})) = \\ &\stackrel{D(X_i) = \sigma_x^2}{=} \beta \frac{1}{n} \sum (X_i - \bar{X})^2 + \beta \frac{1}{n} \sum (X_i - \bar{X})(\xi_i - \bar{\xi}) + \\ &\quad + \frac{1}{n} \sum (\varepsilon_i - \bar{\varepsilon})(X_i - \bar{X}) + \frac{1}{n} \sum (\varepsilon_i - \bar{\varepsilon})(\xi_i - \bar{\xi}) = \\ &= \beta \frac{1}{n} \sum (X_i - \bar{X})^2 \xrightarrow[\text{здесь } \beta_{\text{min}}]{=} \beta \sigma_x^2 \end{aligned}$$

значит  $\hat{\beta}_{\text{min}}$

$$\begin{aligned} \frac{1}{n} \sum (X'_i - \bar{X}')^2 &= \frac{1}{n} \sum ((X_i - \bar{X}) + (\xi_i - \bar{\xi}))^2 = \\ &= \frac{1}{n} \sum (X_i - \bar{X})^2 + 2 \frac{1}{n} \sum (X_i - \bar{X})(\xi_i - \bar{\xi}) + \frac{1}{n} \sum (\xi_i - \bar{\xi})^2 = \\ &= \frac{1}{n} \sum (X_i - \bar{X})^2 + \frac{1}{n} \sum (\xi_i - \bar{\xi})^2 \xrightarrow{=} \sigma_x^2 + \sigma_\xi^2 \end{aligned}$$

Но  $\sigma_\xi$  Случайно.

$$\hat{\beta}_{\text{min}} \xrightarrow{P} \frac{\beta \sigma_x^2}{\sigma_x^2 + \sigma_\xi^2} = \beta \frac{\sigma_x^2}{\sigma_x^2 + \sigma_\xi^2} \leftarrow \beta$$

т.е. оценка несмещенна  $\Rightarrow$  не состоятельна

№4

$$y_i = \alpha x_i + \beta w_i + e_i$$

$$\frac{1}{n} \sum_{i=1}^n x_i x_i^\top \xrightarrow{D} E[x_i x_i^\top] = Q$$

$$X_i = (x_i, w_i)^\top$$

$$\frac{1}{n} \sum_{i=1}^n x_i e_i \xrightarrow{d} N(0, \sigma_e^2 Q)$$

$$Q = E \left[ \begin{pmatrix} x \\ w \end{pmatrix} \begin{pmatrix} x & w \end{pmatrix}^\top \right] = \begin{pmatrix} q_{xx} & q_{xw} \\ q_{wx} & q_{ww} \end{pmatrix}$$

$$Q^{-1} = \frac{1}{q_{xx} q_{ww} - q_{wx}^2} \begin{pmatrix} q_{ww} & -q_{xw} \\ -q_{wx} & q_{xx} \end{pmatrix}$$

Нормальная регрессия (коэф. при  $w_i$  знакои):

$$\begin{pmatrix} \hat{\alpha}_f \\ \hat{\beta}_f \end{pmatrix} = \left( \frac{1}{n} \sum_{i=1}^n X_i X_i^\top \right)^{-1} \sum_{i=1}^n X_i y_i, \quad y_i = \alpha x_i + \beta w_i + e_i$$

$$\begin{pmatrix} (\hat{\alpha}_f - \alpha) \\ (\hat{\beta}_f - \beta) \end{pmatrix} = \left( \frac{1}{n} \sum_{i=1}^n X_i X_i^\top \right)^{-1} \left( \frac{1}{n} \sum_{i=1}^n X_i e_i \right)$$

$$\sqrt{n} \begin{pmatrix} (\hat{\alpha}_f - \alpha) \\ (\hat{\beta}_f - \beta) \end{pmatrix} = \left( \frac{1}{n} \sum_{i=1}^n X_i X_i^\top \right)^{-1} \left( \frac{1}{n} \sum_{i=1}^n X_i e_i \right) \xrightarrow{d} N(0, \sigma_e^2 Q)$$

Простая регрессия:  $y_i = \hat{\alpha} x_i + u_i$

$$\hat{\alpha}_s = \frac{\sum x_i y_i}{\sum x_i^2} = \alpha + \beta \frac{\sum x_i w_i}{\sum x_i^2} + \frac{\sum x_i e_i}{\sum x_i^2}$$

$$\sqrt{n} (\hat{\alpha}_s - \alpha) = \beta \sqrt{n} \frac{\frac{1}{n} \sum x_i w_i}{\frac{1}{n} \sum x_i^2} + \frac{\frac{1}{n} \sum x_i e_i}{\frac{1}{n} \sum x_i^2}, \quad \text{но } \beta = \frac{\sum x_i w_i}{\sum x_i^2} = \frac{\frac{1}{n} \sum x_i w_i}{\frac{1}{n} \sum x_i^2}$$

$$\sqrt{n} (\hat{\alpha}_s - \alpha) \xrightarrow{d} N \left( \beta \cdot \frac{q_{xw}}{q_{xx}}, \frac{\sigma_e^2}{q_{xx}} \right)$$

$$\sqrt{n} (\hat{\alpha}_s - \alpha) \xrightarrow{d} N \left( \beta \cdot \frac{q_{xw}}{q_{xx}}, \frac{\sigma_e^2}{q_{xx}} \right)$$

Используем гипотезы для проверки значимости  $\beta$ :

$H_0: \beta = 0$  в линейной регрессии

$$T_n = \frac{\hat{\beta}_f}{\text{se}(\hat{\beta}_f)} = \frac{T_n \hat{\beta}_f}{\sqrt{\text{se}^2(Q)}} \approx \frac{T_n \beta_f + Z_{\beta}}{\sqrt{\text{se}^2(Q)}} \quad \text{где } Z_{\beta} \sim N(0, \text{se}^2(Q))$$

$$T_n \Big| \begin{matrix} \beta_f = \frac{b}{n} \\ d \end{matrix} \xrightarrow{\text{d}} \frac{b + Z_{\beta}}{\sqrt{\text{se}^2(Q)}} = \frac{b}{\sqrt{\text{se}^2(Q)}} + Z \quad \text{где } Z \sim N(0, 1)$$

Тогда при  $|T_n| > c$  (крит. зона, назначена по  $Z_f$ , where  $d$ )

$$\text{тогда } T_n (Z_f - d) = \begin{cases} \sqrt{n}(Z_f - d), & |T_n| > c \\ \sqrt{n}(Z_c - d), & T_n \leq c \end{cases}$$

Следовательно  $P(|Z + \frac{b}{\sqrt{\text{se}^2(Q)}}| > c)$  — если проверка отклонение  $H_0$ , то

$$\sqrt{n}(Z_f - d) \xrightarrow{\text{d}} \begin{cases} N(0, \text{se}^2(Q^{-1})) & , P \\ N(b \cdot \frac{\text{se}^2(Q^{-1})}{Q_{\text{max}}}, \frac{\text{se}^2(Q^{-1})}{Q_{\text{max}}}) & , 1-P \end{cases}$$