

- Characterize the effect of an i th observation on the OLS estimate.

$$(A - XX')^{-1} = A^{-1} + A^{-1}X(I - X'A^{-1}X)^{-1}X'A^{-1}$$

$$\begin{aligned} (A - XX')(A - XX')^{-1} &= (A - XX')(A^{-1} + A^{-1}X(I - X'A^{-1}X)^{-1}X'A^{-1}) \\ &= AA^{-1} + \underline{AA^{-1}X(I - X'A^{-1}X)^{-1}X'A^{-1}} - \underline{XX'A^{-1}} - \underline{XXA^{-1}X(I - X'A^{-1}X)^{-1}X'A^{-1}} \\ &= I + \underline{X\{I - X'A^{-1}X\}}(I - X'A^{-1}X)^{-1}X'A^{-1} - \underline{XX'A^{-1}} \\ &= I + XX'A^{-1} - XX'A^{-1} = I. \end{aligned}$$

Using the above,

$$\begin{aligned} \hat{\beta}_{(i)} &= (X_{(i)}'X_{(i)})^{-1}X_{(i)}'Y_{(i)} & X_{(i)}: \text{the matrix that does not have observation "i"} \\ &= (X'X - x_i x_i')^{-1}(X'Y - x_i y_i) & X'X = \sum_{j=1}^N x_j x_j' \rightarrow X_{(i)}'X_{(i)} = \sum_{j=1}^N x_j x_j' - x_i x_i' \\ & & X'Y = \sum_{j=1}^N x_j y_j \rightarrow X_{(i)}'Y_{(i)} = \sum_{j=1}^N x_j y_j - x_i y_i \\ &\downarrow \\ &= (X'X - x_i x_i')^{-1} \\ &= (X'X)^{-1} + (X'X)^{-1}x_i(1 - x_i'(X'X)^{-1}x_i)^{-1}x_i'(X'X)^{-1} \\ &= \left[(X'X)^{-1} + (X'X)^{-1}x_i(1 - x_i'(X'X)^{-1}x_i)^{-1}x_i'(X'X)^{-1} \right] (X'Y - x_i y_i) \\ &= \left\{ (X'X)^{-1} + \frac{(X'X)^{-1}x_i x_i'(X'X)^{-1}}{1 - x_i'(X'X)^{-1}x_i} \right\} (X'Y - x_i y_i) \\ &= \overbrace{(X'X)^{-1}X'Y}^{\hat{\beta}} - (X'X)^{-1}x_i y_i + \frac{(X'X)^{-1}x_i x_i'(X'X)^{-1}X'Y}{1 - x_i'(X'X)^{-1}x_i} - \frac{(X'X)^{-1}x_i \overbrace{x_i'(X'X)^{-1}x_i}^{\text{scalar}} x_i y_i}{1 - x_i'(X'X)^{-1}x_i} \\ &= \hat{\beta} - (X'X)^{-1}x_i y_i \left(1 + \frac{x_i'(X'X)^{-1}x_i}{1 - x_i'(X'X)^{-1}x_i} \right) + \frac{(X'X)^{-1}x_i x_i' \hat{\beta}}{1 - x_i'(X'X)^{-1}x_i} \\ &= \hat{\beta} - (X'X)^{-1}x_i y_i \left(\frac{1}{1 - x_i'(X'X)^{-1}x_i} \right) + \frac{(X'X)^{-1}x_i x_i' \hat{\beta}}{1 - x_i'(X'X)^{-1}x_i} \\ &= \hat{\beta} - (X'X)^{-1}x_i \left(\frac{y_i - x_i' \hat{\beta}}{1 - x_i'(X'X)^{-1}x_i} \right) = \hat{\beta} - \frac{(X'X)^{-1}x_i \hat{u}_i}{1 - x_i'(X'X)^{-1}x_i} \quad \therefore \hat{\beta} - \hat{\beta}_{(i)} = \frac{(X'X)^{-1}x_i \hat{u}_i}{1 - x_i'(X'X)^{-1}x_i} \end{aligned}$$

$$\hat{\beta} - \hat{\beta}_{(i)} = \frac{(X'X)^{-1}x_i \hat{u}_i}{1 - x_i'(X'X)^{-1}x_i}$$

→ If this is close to "1", the gap is big
If "0", "small."

$$(A + XX')^{-1} = A^{-1} - A^{-1}X(I + XA^{-1}X)^{-1}X'A^{-1}$$

$$\hat{\beta} = (X'X)^{-1}X'Y = (X'_{(i)}X_{(i)} + x_i x_i')(X'_{(i)}Y_{(i)} + x_i y_i)$$

$$= [(X'_{(i)}X_{(i)})^{-1} - (X'_{(i)}X_{(i)})^{-1}x_i \{1 + x_i'(X'_{(i)}X_{(i)})^{-1}x_i\}^{-1}x_i'(X'_{(i)}X_{(i)})^{-1}] (X'_{(i)}Y_{(i)} + x_i y_i)$$

$$= (X'_{(i)}X_{(i)})^{-1}X'_{(i)}Y_{(i)} + (X'_{(i)}X_{(i)})^{-1}x_i y_i - \frac{(X'_{(i)}X_{(i)})^{-1}x_i x_i' \hat{\beta}_{(i)}}{1 + x_i'(X'_{(i)}X_{(i)})^{-1}x_i} - \frac{(X'_{(i)}X_{(i)})^{-1}x_i [x_i'(X'_{(i)}X_{(i)})^{-1}x_i]}{1 + x_i'(X'_{(i)}X_{(i)})^{-1}x_i}$$

$$= \hat{\beta}_{(i)} + \frac{(X'_{(i)}X_{(i)})^{-1}x_i [y_i - x_i' \hat{\beta}_{(i)}]}{1 + x_i'(X'_{(i)}X_{(i)})^{-1}x_i} = \hat{\beta}_{(i)} + \frac{(X'_{(i)}X_{(i)})^{-1}x_i \hat{u}_i}{1 + x_i'(X'_{(i)}X_{(i)})^{-1}x_i}$$

$$\hat{\beta} - \hat{\beta}_{(i)} = \frac{(X'_{(i)}X_{(i)})^{-1}x_i \hat{u}_i}{1 + x_i'(X'_{(i)}X_{(i)})^{-1}x_i}$$

$$x_i' \hat{\beta} - x_i' \hat{\beta}_{(i)} = \frac{x_i'(X'_{(i)}X_{(i)})^{-1}x_i}{1 + x_i'(X'_{(i)}X_{(i)})^{-1}x_i} (y_i - x_i' \hat{\beta}_{(i)})$$

$$\underbrace{\frac{x_i'(X'_{(i)}X_{(i)})^{-1}x_i}{1 + x_i'(X'_{(i)}X_{(i)})^{-1}x_i}}_{(*)} \quad 0 \leq \frac{(*)}{1 + (*)} \leq 1 \quad \text{If } (*) \text{ is very large, } \frac{(*)}{1 + (*)} \rightarrow 1$$

↓
This means the variance of x_i is large

Estimate $x_i' \beta$ for a given x_i by OLS $x_i' \hat{\beta}_{(i)}$

$$b^+ x_i'(X'_{(i)}X_{(i)})^{-1}x_i$$

→ If $x_i' \beta$ is difficult to estimate,

we can understand there exists the effect from i like above.

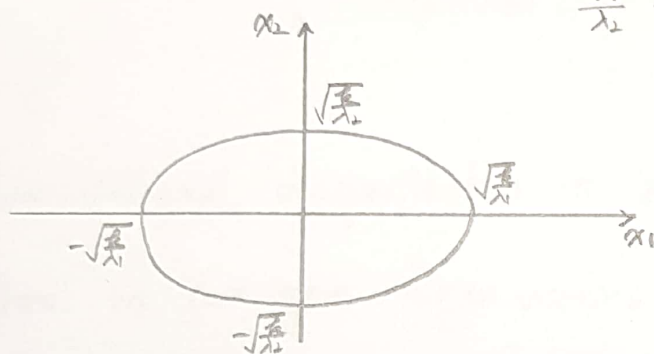
Think of a quadratic form of $x'(\lambda_1 \lambda_2)^{-1}x$

Assume its dimension is 2.

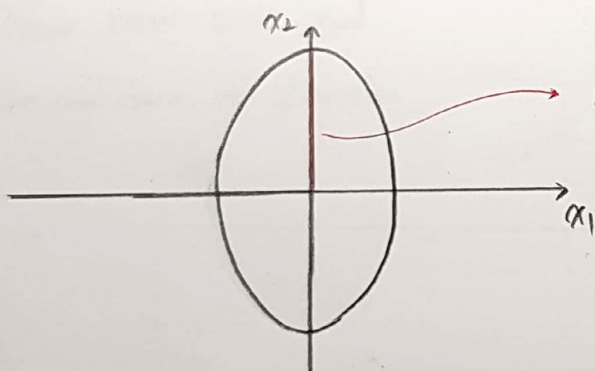
$$\text{Then, } (x_1 \ x_2) \begin{pmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \lambda_1 x_1^2 + \lambda_2 x_2^2 = k.$$

i.e.,

$$\frac{x_1^2}{\frac{k}{\lambda_1}} + \frac{x_2^2}{\frac{k}{\lambda_2}} = \frac{k}{\lambda_1 \lambda_2} \quad \text{i.e.,} \quad \frac{x_1^2}{\frac{k}{\lambda_1}} + \frac{x_2^2}{\frac{k}{\lambda_2}} = 1$$



$$\downarrow \quad \begin{pmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{pmatrix}^{-1} = \begin{pmatrix} \frac{1}{\lambda_1} & 0 \\ 0 & \frac{1}{\lambda_2} \end{pmatrix} \quad \text{by inverse}$$



So, we can understand

\exists high influence from x_2 .

When is $x'(\lambda_1 \lambda_2)^{-1}x$ "large"?

$$= \|x\|^2 \left[\frac{x'(\lambda_1 \lambda_2)^{-1}x}{\|x\|^2} \right] \quad : \quad x \text{ is normalized by } \|x\|.$$

(Thus, if $\|x\|^2$ is big, $x'(\lambda_1 \lambda_2)^{-1}x$ is big)

In order to know which direction is bigger,

$$\max_{x_i} x_i'(\lambda_1 \lambda_2)^{-1}x_i \quad \text{s.t.} \quad \|x_i\| = 1$$

Then, $x_i'(\lambda_1 \lambda_2)^{-1}x_i$ maximized at the eigen-vector corresponding to the maximum eigen-value of $(\lambda_1 \lambda_2)^{-1}$

$$X_i' (X_i' X_i)^{-1} X_i$$

$X_i' X_i$: symmetric.
:= A.

$$X_i' A X_i = (Qy)' A (Qy) = y' Q' A Q y = y' D y \text{ where } Q' A Q = D$$

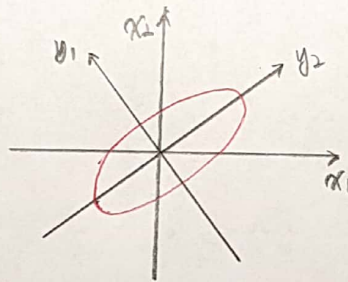
$$= (y_1 \dots y_N) \begin{pmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \ddots & & \\ \vdots & & \ddots & \\ 0 & \dots & 0 & \lambda_N \end{pmatrix} \begin{pmatrix} y_1 \\ \vdots \\ y_N \end{pmatrix} = \lambda_1 y_1^2 + \dots + \lambda_N y_N^2$$

① Take orthogonal diagonalization to $X_i' X_i$

Then, we can get eigen vectors and $Q = [V_1 \dots V_N]$ where $\|V_i\|=1$.

② Set $|Q|=1$, then Q -unit vectors will be new axis.

③ Draw new axis and
We can know its direction.



ex)

$$\log wage = \underset{(0.14)}{0.284} + \underset{(0.007)}{0.092 \text{ educ}} + \underset{(0.0017)}{0.0041 \text{ exper}} + \underset{(0.03)}{0.022 \text{ tenure}}$$

$$H_0: \beta_{\text{exper}} = 0 \quad v. \quad H_1: \beta_{\text{exper}} > 0.$$

$$t_{\text{exper}} = \frac{0.0041}{0.0017} \approx 2.41, \text{ reject } H_0. \quad (2.41 > 1.96 \text{ 95\% confi. interval})$$