

$$Y = f(\underline{x}) + \underbrace{\varepsilon}_{\text{error}}$$

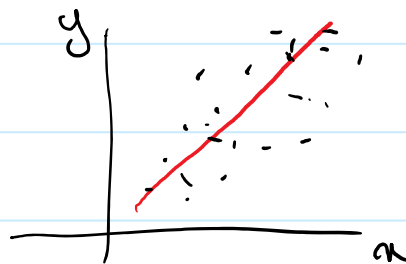
$$E(\varepsilon) = 0$$

\underline{x} and ε are independent

$Y = f(x) \rightarrow$ deterministic relationship

$$Y = \beta_0 + \beta_1 x + \varepsilon$$

$$f(x) = \beta_0 + \beta_1 x$$



$$\hat{f}(x) = \hat{\beta}_0 + \hat{\beta}_1 x$$

Slide 10

$$E(Y - \hat{Y})^2 = E(f(\underline{x}) + \varepsilon - \hat{f}(\underline{x}))^2$$

$$= E(f(\underline{x}) - \hat{f}(\underline{x}) + \varepsilon)^2$$

$$= E\left\{(f(\underline{x}) - \hat{f}(\underline{x}))^2 + \varepsilon^2\right.$$

$$\left. + 2(f(\underline{x}) - \hat{f}(\underline{x}))\varepsilon\right\}$$

$$= E(f(\underline{x}) - \hat{f}(\underline{x}))^2 + E(\varepsilon^2)$$

$$+ 2 \underbrace{E(f(\underline{x}) - \hat{f}(\underline{x})) E(\varepsilon)}_{\text{indep of } \varepsilon \text{ and } \underline{x}}$$

Week 1- Slide 10 Cont.

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we know that $E(\epsilon) = 0$

$$E(Y - \hat{Y})^2 = E(f(x) - \hat{f}(x))^2 + E(\epsilon^2)$$

$\text{Var}(\epsilon) = E(\epsilon^2) - \underbrace{(E(\epsilon))^2}_0$

$$= \underbrace{(f(x) - \hat{f}(x))^2}_{\text{reducible error}} + \underbrace{\text{Var}(\epsilon)}_{\text{irreducible error}}$$

MLE and MLE of Poisson

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MLE

Y_1, \dots, Y_n , Y_i follows $f_i(y_i; \theta)$
joint density: $f(\underline{y}; \theta)$
 $\underline{y} \in \mathbb{R}^p$

We want to estimate θ :

likelihood function $L(\theta; \underline{y})$

maximize $L(\theta; \underline{y})$
 $\theta \in \Theta$ \rightarrow parameter space

if Y_i 's are indep $f(\underline{y}; \theta) = \prod_{i=1}^n f_i(y_i; \theta)$

instead of working with $L(\theta; \underline{y})$, try to maximize $\ln(L(\theta; \underline{y}))$

example Poisson dist (slide 15) $P(\theta)$

$$f_Y(y; \theta) = \frac{e^{-\theta} \theta^y}{y!}$$

$Y_1, \dots, Y_n \stackrel{iid}{\sim} P(\theta)$

$$f(\underline{y}; \theta) = \prod_{i=1}^n \frac{e^{-\theta} \theta^{y_i}}{y_i!}$$

MLE of Poisson Cont.

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$$L(\theta) = \prod_{i=1}^n \frac{e^{-\theta} \theta^{y_i}}{y_i!} = \frac{e^{-n\theta} \theta^{\sum_{i=1}^n y_i}}{\prod y_i!}$$

$y_i \geq 0$
 Since Poisson variable
 counts the number of
 success in a given
 period of time or
 place

$$\ell(\theta) = \ln(L(\theta)) = -n\theta + \left(\sum_{i=1}^n y_i\right) \ln \theta - \ln \prod y_i!$$

$$\frac{\partial \ell(\theta)}{\partial \theta} = -n + \frac{\sum y_i}{\theta} = 0 \quad \Rightarrow \quad \hat{\theta} = \frac{\sum y_i}{n} = \bar{y}$$

$$\frac{\partial^2 \ell(\theta)}{\partial \theta^2} = - \frac{\sum y_i}{\theta^2} \leq 0$$

MLE of θ

Sufficient Statistics

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$$\epsilon_i \stackrel{iid}{\sim} N(0, \sigma^2)$$

$$Y_i = f(X_i) + \epsilon_i \Rightarrow Y_i \sim N(\underbrace{f(X_i)}_{\beta_0 + \beta_1 x_i}, \sigma^2)$$

sufficiency: $X_1, \dots, X_n \stackrel{iid}{\sim} f(x_i, \theta)$, the statistic $T(X_1, \dots, X_n)$ is sufficient for θ if it contains all the information that can be extracted from X_1, \dots, X_n

e.g. $X_i \sim \text{Binomial}(p)$ MLE of p $\hat{p} = \frac{\sum X_i}{n}$