

DATA MODELING: CSCI E-106

TA SESSION 3



Harvard
University

THE DATA MODELING IS A GRADUATE-LEVEL COURSE!

- Read the syllabus, announcements and piazza; they contain useful info
- Homework should be done on Rstudio.cloud (we cannot accept excuses about home or work computers)
- TA sessions are not review sessions only
- Concept of minimal reproducible example

STATISTICAL SOFTWARE

- Various programs and packages have various methods (and, thus, results)
- Always check with known results
- Read manuals! Use google or stackoverflow.com
- Run examples!

LIKELIHOOD FUNCTION AND ESTIMATION

- From wikipedia: “... likelihood function (often simply the likelihood) is a function of the parameters of a statistical model, given specific observed data. ”

$$\prod_{i=1}^n \mathcal{L}(\text{data}|\text{parameters}) = \prod_{i=1}^n P(\text{data}|\text{parameters})$$

- Different types of estimation (least squares, objective function minimization, moment matching, ... and log-likelihood function minimization)
- Usually we use log-likelihood because taking a derivative of a sum is more convenient

LIKELIHOOD FUNCTION AND ESTIMATION (EXAMPLE)

2.53. (Calculus needed.)

- a. Obtain the likelihood function for the sample observations Y_1, \dots, Y_n given X_1, \dots, X_n , if the conditions on page 83 apply.
- b. Obtain the maximum likelihood estimators of β_0 , β_1 , and σ^2 . Are the estimators of β_0 and β_1 the same as those in (1.27) when the X_i are fixed?

LIKELIHOOD FUNCTION AND ESTIMATION (EXAMPLE)

■ Can we still use regression model (2.1) if Y_1 and Y_2 are not bivariate normal? It can be shown that all results on estimation, testing, and prediction obtained from regression model (2.1) apply if $Y_1 = Y$ and $Y_2 = X$ are random variables, and if the following conditions hold:

1. The conditional distributions of the Y_i , given X_i , are normal and independent, with conditional means $\beta_0 + \beta_1 X_i$ and conditional variance σ^2 .
2. The X_i are independent random variables whose probability distribution $g(X_i)$ does not involve the parameters $\beta_0, \beta_1, \sigma^2$.

$$(Y | X) \sim N(\beta_0 + \beta_1 X, \sigma^2)$$

$$g(X_i | \beta_0, \beta_1, \sigma^2) = g(X_i)$$

LIKELIHOOD FUNCTION AND ESTIMATION (EXAMPLE)

- Obtain likelihood function

$$\prod_{i=1}^n \mathcal{L}(\text{data}|\text{parameters}) = \prod_{i=1}^n P(\text{data}|\text{parameters})$$

$$P(Y = Y_i, X = X_i | \beta_0, \beta_1, \sigma^2)$$

LIKELIHOOD FUNCTION AND ESTIMATION (EXAMPLE)

$$P(Y = Y_i, X = X_i | \beta_0, \beta_1, \sigma^2)$$

$$P(Y = Y_i \cap X = X_i | \beta_0, \beta_1, \sigma^2)$$

- Using the chain rule of probability

$$P(A \cap B) = P(A|B) \cdot P(B)$$

LIKELIHOOD FUNCTION AND ESTIMATION (EXAMPLE)

$$P(Y = Y_i, X = X_i | \beta_0, \beta_1, \sigma^2)$$

$$P(Y = Y_i \cap X = X_i | \beta_0, \beta_1, \sigma^2)$$

- Using the chain rule of probability $P(A \cap B) = P(A|B) \cdot P(B)$

$$\begin{aligned} P(Y = Y_i \cap X = X_i | \beta_0, \beta_1, \sigma^2) &= P(Y = Y_i | X = X_i, \beta_0, \beta_1, \sigma^2) \cdot P(X = X_i | \beta_0, \beta_1, \sigma^2) \\ &= \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left[-\frac{1}{2\sigma^2} (Y_i - \beta_0 - \beta_1 X_i)^2 \right] g(X_i) \end{aligned}$$