

Problem Set 1

Handed out: January 26, 2026
Due: February 4, 2026

1. Maximum Likelihood

(40 points total)

Let X be distributed as $N(\mu, \sigma^2)$. The unknown parameters are μ and σ^2 .

- Find the log-likelihood function $\ell_n(\mu, \sigma^2)$. (8 points)
- Take the first order condition with respect to μ , and show that the solution for $\hat{\mu}$ does not depend on σ^2 . (10 points)
- Define the concentrated log-likelihood function $\ell_n(\hat{\mu}, \sigma^2)$. The concentrated log-likelihood substitutes the MLE $\hat{\mu} = \bar{x}$ from part (b) into the original log-likelihood, treating it as a function of σ^2 only. Take the first order condition with respect to σ^2 , and find the MLE $\hat{\sigma}^2$ for σ^2 . (12 points)
- Generate 1000 observations from $N(\mu = 10, \sigma^2 = 4)$. (10 points)
 - Write an R function `loglik_normal(theta, y)` that computes the log-likelihood, where `theta = c(mu, sigma2)`.
 - Use `optim()` to estimate μ and σ^2 . Use starting values `theta_init = c(0, 1)` and `set.seed(8213)`.
 - Compare your MLE estimates to:
 - The true parameters ($\mu = 10, \sigma^2 = 4$)
 - The sample mean \bar{y} and sample variance $s^2 = \frac{1}{n-1} \sum_{i=1}^n (y_i - \bar{y})^2$

Present your results in a table.

2. Binary Choice Logistic Distribution

(20 points total)

For the logistic distribution $\Lambda(x) = (1 + \exp(-x))^{-1}$, verify that

- $\frac{d}{dx} \Lambda(x) = \Lambda(x)(1 - \Lambda(x))$. (5 points)
- $h_{\text{logit}}(x) = \frac{d}{dx} \log \Lambda(x) = 1 - \Lambda(x)$. (5 points)
- $H_{\text{logit}}(x) = -\frac{d^2}{dx^2} \log \Lambda(x) = \Lambda(x)(1 - \Lambda(x))$. (5 points)
- $|H_{\text{logit}}(x)| \leq 1$. (5 points)

3. Binary Choice Estimation

(40 points total)

The data for Question 3 come from Grogger, J. (1991), "Certainty vs. Severity of Punishment," *Economic Inquiry* 29, 297-309. The dataset `grogger.dta` is available on Canvas.

Dataset description:

- Unit of observation: Individual men
- Sample: Men arrested at least once prior to 1986
- Time period: 1986 arrests and prior criminal history
- Key variables:
 - `narr86`: Number of arrests in 1986
 - `pcnv`: Proportion of prior arrests resulting in conviction (probability of conviction)

- *avgsen*: Average sentence length (months) from prior convictions
 - *totttime*: Total time spent in prison since age 18 (months)
 - *ptime86*: Months spent in prison during 1986
 - *inc86*: Legal income in 1986 (hundreds of dollars)
 - *black*: =1 if black
 - *hispan*: =1 if Hispanic
 - *born60*: =1 if born in 1960 or later
- a) Define a binary variable, *arr86*, equal to unity if a man was arrested at least once during 1986, and zero otherwise. Estimate an LPM relating *arr86* to *pcnv*, *avgsen*, *totttime*, *ptime86*, *inc86*, *black*, *hispan*, and *born60*. Report the usual and heteroskedasticity-robust standard errors. What is the estimated effect on the probability of arrest if *pcnv* goes from .25 to .75? **(8 points)**
- b) Test the joint significance of *avgsen* and *totttime*, using a nonrobust and robust test. **(6 points)**
- c) Now estimate the model by probit. At the average values of *avgsen*, *totttime*, *inc86*, and *ptime86* in the sample, and with *black* = 1, *hispan* = 0, and *born60* = 1, what is the estimated effect on the probability of arrest if *pcnv* goes from .25 to .75? Compare this result with the answer from part a. **(8 points)**
- d) For the probit model estimated in part c, obtain the percent correctly predicted. What is the percent correctly predicted when *narr86* = 0? When *narr86* = 1? What do you make of these findings? **(8 points)**
- e) In the probit model, add the terms $pcnv^2$, $ptime86^2$, and $inc86^2$ to the model. Are these individually or jointly significant? Describe the estimated relationship between the probability of arrest and *pcnv*. In particular, at what point does the probability of conviction have a negative effect on probability of arrest? **(10 points)**