

Lecture 4

HW 1 up

L II Max L-

ch 4 Max L

Max Likelihood Principle
ML 4 discrete S

Lecture Notes II – Maximum Likelihood Estimation for Discrete Distributions

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Max Likelihood Principle ←

ML estimation for arbitrary discrete distributions ←

Other ML estimation examples

ML estimate as a random variable

Reading: Ch. 4.1, 4.2

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Maximum Likelihood Principle

Ex Language models

English

$$\mathcal{P}^E = (\theta_a^E, \theta_b^E, \dots, \theta_z^E)$$

$\parallel$
 $\mathcal{P}^E(a)$

Spanish $\mathcal{P}^S = (\theta_a^S, \theta_b^S, \dots)$

French $\mathcal{P}^F = (\theta_a^F, \theta_b^F, \dots)$

Sentence

Data $\uparrow$

statistics = $x^1 \dots x^n$

$\downarrow \quad \downarrow$
 $x^{(1)} \quad x^{(2)}$
 $\cap \quad \cap$
 $S \quad S$

$$S = \{a, b, c, \dots, z\}$$

$$m = |S| = 26$$

$$\mathcal{P}^E(\{a\}) = \mathcal{P}^E(a)$$

Maximum Likelihood Principle = choose "model" that make data parameters most likely (=probable)

Q: Language = ?

Answer $\in \{E, F, S, G\} = \mathcal{M}$

$P^E(\text{Statistics}) = L(E)$ likelihood $\ln L(E) = l(E)$
log-likelihood

$P^F(-u-) = L(F)$

...

$\log_2 \rightarrow l(E) = -38.6 \Leftrightarrow P^E(\text{statistics}) = 2^{-38.6}$

$l(F) = -38.3 \rightarrow \max \Rightarrow \underline{\underline{\text{Answer} = F}}$

$l(G) = -39.8$

...

It's a guess !!!

Maximum Likelihood Principle

Data $\mathcal{D} = \{x^1, \dots, x^n\} \sim \text{iid } S$ with unknown P on S

Model class = {all possible P 's to consider}

Belief about P

Inference $P^{ML} \in \mathcal{M}$

Estimation

$\mathcal{M}$

Max likelihood

$$P^{ML} = \underset{P \in \mathcal{M}}{\operatorname{argmax}} P(\mathcal{D}) = \underset{P \in \mathcal{M}}{\operatorname{argmax}} L(P; \mathcal{D})$$

likelihood of $\mathcal{D}$ under P

ML estimation for arbitrary discrete distributions (finite S)

Model class

$$S = \{1, 2, \dots, m\}$$

$$\mathcal{M} = \{(\theta_{1:m}) \text{ with } \theta_j \geq 0 \text{ for all } j, \sum_{j=1}^m \theta_j = 1\}$$

any P on S defined by $\theta_1, \theta_2, \dots, \theta_m$ parameters

$$\left[\begin{array}{l} \theta_j = P(j) \geq 0 \\ \sum_{j=1}^m \theta_j = 1 \end{array} \right.$$

Data $\mathcal{D} = \{x^1, \dots, x^n\} \subset S$

Ex: Coin toss $S = \{0, 1\}$ $\mathcal{M} = \{(\theta_0, \theta_1), \theta_0 + \theta_1 = 1, \theta_{0,1} \geq 0\}$

$$\mathcal{D} = 1, 0, 1, 1, 0 \Rightarrow L(\theta) = \underbrace{\theta_1}_{n_1} \underbrace{\theta_0}_{n_0} \underbrace{\theta_1}_{n_1} \underbrace{\theta_1}_{n_1} \underbrace{\theta_0}_{n_0} = \theta_0^{n_0} \theta_1^{n_1}$$

$n=5$ $n_1=3$ $n_0=2$

0. S_1 Model class $\mathcal{M}$

ML estimation for arbitrary discrete distributions

1. Write likelihood

$$L(\theta) \equiv P(\mathcal{D} | \theta) = \prod_{i=1}^n \underbrace{P(x^i | \theta)}_{\theta_{x^i}} = \prod_{i=1}^n \theta_{x^i} = \theta_1^{n_1} \theta_2^{n_2} \dots \theta_m^{n_m}$$

$$\text{if } x_i = j \Rightarrow \theta_j$$

- $n_j = \# \{x^i = j\}$ counts
 $j = 1:m$

$$= \prod_{j=1}^m \theta_j^{n_j}$$

1.' Log likelihood

$$l(\theta) = \ln L(\theta) = \sum_{j=1}^m n_j \ln \theta_j$$

Annotations:
- n_j is labeled "data" (green arrow).
- θ_j is labeled "unknowns" (yellow arrow).

2. Find $\theta^{\text{ML}} = \underset{\theta \in \mathcal{M}}{\operatorname{argmax}} l(\theta) \equiv \underset{\theta \in \mathcal{M}}{\operatorname{argmax}} L(\theta)$

STATISTICS

CALCULUS

ML estimation for arbitrary discrete distributions

$m=2$ (from Ex)

$$n_0 = 2$$

$$n_1 = 3$$

$$L(\theta) = \theta_0^2 \theta_1^3$$

$$l(\theta) = 2 \cdot \ln \theta_0 + 3 \cdot \ln(\theta_1)$$

1. write L for generic θ

2. calculus

$\theta_0, \theta_1 = \arg \max$

$$\theta_0 = 1 - \theta_1 \quad \max_{\theta_1} 2 \ln(1 - \theta_1) + 3 \ln(\theta_1) = l(\theta)$$

$$l'(\theta_1) = 2 \cdot \frac{-1}{1 - \theta_1} + 3 \cdot \frac{1}{\theta_1} = 0 \quad | \quad x \theta_1, (1 - \theta_1)$$

$$-2\theta_1 + 3(1 - \theta_1) = 0 \quad \text{in general}$$

$$3 = 5\theta_1 \Rightarrow \theta_1^{\text{ML}} = \frac{3}{5} = \frac{n_1}{n}$$

$$\theta_0^{\text{ML}} = \frac{2}{5} = \frac{n_0}{n}$$

+ verify $l(\theta^{\text{ML}})$ is max
e.g. $l''(\theta^{\text{ML}}) < 0$

$$(\ln z)' = \frac{1}{z}$$

Other ML estimation examples

$$S = \{1, \dots, m\} \quad m > 2$$

$$\mathcal{D} = \{x^1, \dots, x^n\} \subset S$$

$$\mathcal{M} = \{(\theta_1, \dots, \theta_m), \theta_j \geq 0 \text{ for all } j, \sum \theta_j = 1\} \quad \text{constraint}$$

$$1. \text{ Write } L(\theta) = \theta_1^{n_1} \theta_2^{n_2} \dots \theta_m^{n_m}$$

$$1'. \text{ log-L } l(\theta) = \underbrace{n_1}_{\text{from } \mathcal{D}} \ln \theta_1 + \dots + \underbrace{n_m}_{\text{from } \mathcal{D}} \ln \theta_m \quad \leftarrow m \text{ unknowns}$$

$$\text{Ex } S = \{1, \dots, 6\}$$

$$\text{die roll } n = 9$$

$$\mathcal{D} = \underline{5}, \underline{3}, \underline{3}, \underline{1}, \underline{2}, \underline{4}, \underline{6}, \underline{5}, \underline{1}$$

$$n_1 = n_3 = n_5 = 2$$

$$n_2 = n_4 = n_6 = 1$$

$$l = 2 \ln \theta_1 + 1 \ln \theta_2 + 2 \ln \theta_3 + 1 \ln \theta_4 + 2 \ln \theta_5 + 1 \ln \theta_6$$

$$2. \theta_{1:6}^{\text{ML}} = \underset{\theta_{1:6}}{\operatorname{argmax}} l(\theta) \quad \text{subject to } \ast \text{ constraints}$$

Maximization with constraints $\leftarrow$ Lagrange multipliers

START $\downarrow$
CALC $\downarrow$

Other ML estimation examples

$$l(\theta) = \sum_{j=1}^n n_j \ln \theta_j \quad \leftarrow \text{argmax s.t.} *$$

Solution by Lagrange multiplier method

$$\max_{\lambda, \theta_{1:m}} l(\theta) + \lambda \left(\sum_{j=1}^m \theta_j - 1 \right)$$

$\lambda, \theta_{1:m}$ $\rightarrow$ $m+1$ unknowns $m+1$ variables
 λ $\rightarrow$ new variable λ
 $\left(\sum_{j=1}^m \theta_j - 1 \right)$ $\rightarrow$ linear in λ
 $\lambda(\dots)$ $\rightarrow$ constraint
 n_j $\rightarrow$ data

$$\frac{\partial l}{\partial \theta_j} = \frac{\partial}{\partial \theta_j} \left[\sum_{l=1}^m n_l \ln \theta_l + \lambda \sum_{l=1}^m \theta_l - 1 \right] = \frac{n_j}{\theta_j} + \lambda = 0$$

$$\Rightarrow \theta_j = -\frac{n_j}{\lambda}$$

$$\frac{\partial l}{\partial \lambda} = \sum_{j=1}^n \theta_j - 1 = 0 \Rightarrow \sum \theta_j = 1$$

$$\lambda = -n \Rightarrow \theta_j^{ML} = \frac{n_j}{n}$$

$$\sum \theta_j = -\frac{\sum n_j}{\lambda} = -\frac{n}{\lambda} \geq 0$$

Other ML estimation examples

$$\theta_j^{ML} = \frac{n_j}{n} \quad j=1, \dots, m$$

sufficient statistics

$n_{1:m}$ known $\leftrightarrow \theta_{1:m}$ known

$$S = \{1, \dots, m\}$$

statistic function of $\mathcal{D}$
function of $x \in S$

r.v. useful for estimation

STAT
PROB $\in$ MATH

$$f: S \rightarrow \mathbb{R}$$

random variables
Probability

$$\mathcal{D} \rightarrow n_{1:m} \rightarrow \theta^{ML}$$

ML estimation

$$|\mathcal{D}| = n$$

$\exists$ sufficient statistics

Exponential family

finite S categorical

Normal

Poisson

uniform