

CMPUT 466 Assignment 4

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Problem 1

If $P(X, Y) = f(X)g(Y)$ for some function f on X only, then X and Y are independent.

Proof. Using marginal probability,

$$\begin{aligned} P(X)P(Y) &= \int_X P(X, Y)dX \int_Y P(X, Y)dY \\ &= \int_X f(X)g(Y)dX \int_Y f(X)g(Y)dY \\ &= f(X)g(Y) \int_X f(X)dX \int_Y g(Y)dY \\ &= P(X, Y) \int_X f(X)dX \int_Y g(Y)dY \\ &= P(X, Y) \end{aligned}$$

Thus, we have proven that if $P(X, Y) = f(X)g(Y)$, $P(X, Y) = P(X)P(Y)$.

This is the definition for independent random variables, so X and Y must be independent.

The proof is similar in the discrete case, just replace \int with \sum

□

Problem 2

$\mathbb{E}_{X \sim P(X)}[af(X) + bg(X)]$ is a linear system.

Proof. Using the definition for \mathbb{E} ,

$$\begin{aligned} \mathbb{E}_{X \sim P(X)}[af(X) + bg(X)] &= \sum_X P(X)(af(X) + bg(X)) \\ &= \sum_X aP(X)f(X) + \sum_X bP(X)g(X) \end{aligned}$$

$$= a \sum_X P(X) f(X) + b \sum_X P(X) g(X)$$

applying the definition again,

$$\mathbb{E}_{X \sim P(X)}[af(X) + bg(X)] = a\mathbb{E}_{X \sim P(X)}[f(X)] + b\mathbb{E}_{X \sim P(X)}[g(X)]$$

This precisely fits the definition of a linear system. The proof is similar in the continuous case, just replace \sum with \int □

Problem 3

- $X \sim U[a, b]$ continuous random variable
- uniformly distributed
- a, b unknown parameters
- dataset $\{x^{(m)}\}_{m=1}^M$

a) Likelihood of parameters

because of the above information,

$$\mathcal{L}(a, b; \mathcal{D}) = \prod_{m=1}^m \frac{1}{b-a} = \frac{1}{(b-a)^m}$$

- note: if $x^{(m)} = a = b$, then the likelihood is infinite
- if $x^{(m)} \notin [a, b]$, then the likelihood is zero

The log likelihood is:

$$\log \frac{1}{(b-a)^m} = -m \log(b-a)$$

b) MLE of parameters

- the derivative of the log likelihood with respect to a is $\frac{m}{b-a}$
 - we notice that this is monotonically increasing, so MLE for a is the largest a possible, i.e.

$$\hat{a} = \min_m \{x^{(m)}\}$$

- the derivative of the log likelihood with respect to b is $-\frac{m}{b-a}$
 - we notice that this is monotonically decreasing, so MLE for b is the smallest b possible, i.e.

$$\hat{b} = \max_m \{x^{(m)}\}$$

Problem 4

c) Prove MLE is biased in this case

- let $B \in [a, b]$

Then,

$$\begin{aligned} Pr[\hat{b} \leq B] &= \Pi_{m=1}^M Pr[x^{(m)} \leq B] \\ &= \left(\frac{B - a_*}{b_* - a_*} \right)^M \end{aligned}$$

This is the cumulative probability density function $F_{\hat{b}}(B)$

$$f_{\hat{b}}(B) = \frac{d}{dB} F_{\hat{b}}(B) = M \frac{(B - a_*)^{(M-1)}}{(b_* - a_*)^M}$$

$$\begin{aligned} \mathbb{E}_{x^{(m)} \sim iid U[a_*, b_*]}[\hat{b}] &= \int_{a_*}^{b_*} \frac{\hat{b} M (\hat{b} - a_*)^{(M-1)}}{(b_* - a_*)^M} d\hat{b} \\ &= \frac{M}{(b_* - a_*)^M} \int_{a_*}^{b_*} \hat{b} (\hat{b} - a_*)^{(M-1)} d\hat{b} \\ &= \frac{M}{(b_* - a_*)^M} \int_{a_*}^{b_*} a_* (\hat{b} - a_*)^{(M-1)} + (\hat{b} - a_*)^M d\hat{b} \\ &= \frac{M}{(b_* - a_*)^M} \left(a_* \int_{a_*}^{b_*} (\hat{b} - a_*)^{(M-1)} d\hat{b} + \int_{a_*}^{b_*} (\hat{b} - a_*)^M d\hat{b} \right) \\ &= \frac{M}{(b_* - a_*)^M} \left(\frac{a_* (\hat{b} - a_*)^M}{M} \Big|_{a_*}^{b_*} + \frac{(\hat{b} - a_*)^{(M+1)}}{M+1} \Big|_{a_*}^{b_*} \right) \\ &= \frac{M}{(b_* - a_*)^M} \left(\frac{a_* (b_* - a_*)^M}{M} + \frac{(b_* - a_*)^{(M+1)}}{M+1} \right) \\ &= a_* + \frac{M(b_* - a_*)}{M+1} \\ &\neq b_* \end{aligned}$$

This proves that the MLE is biased.

Similarly, we can see that:

$$\mathbb{E}[\hat{a}] = a_* + \frac{b_* - a_*}{M+1}$$

, which is $\neq a_*$

d) Prove MLS is asymptotically unbiased if $M \rightarrow +\infty$

$$\begin{aligned}\lim_{M \rightarrow \infty} \mathbb{E}[\hat{a}] &= \lim_{M \rightarrow \infty} a_* + \frac{b_* - a_*}{M + 1} \\ &= a_*\end{aligned}$$

$$\begin{aligned}\lim_{M \rightarrow \infty} \mathbb{E}[\hat{b}] &= \lim_{M \rightarrow \infty} a_* + \frac{M(b_* - a_*)}{M + 1} \\ &= \lim_{M \rightarrow \infty} \frac{(a_*M + a_*) + b_*M - a_*M}{M + 1} \\ &= \lim_{M \rightarrow \infty} \frac{a_*}{M + 1} + \frac{b_*M}{M + 1} \\ &= 0 + b_* \\ &= b_*\end{aligned}$$

This proves that as $M \rightarrow +\infty$, $\mathbb{E}[\hat{a}] = a$ and $\mathbb{E}[\hat{b}] = b$, which fits the definition for unbiased.

- note: $x^{(m)} \sim^{iid} U[a_*, b_*]$ should be under the \mathbb{E} symbols but was dropped for brevity