Assignment 3: Exponential families, conjugacy, and entropy

Stat 348, Spring 2023

Instructions: Submit a well-formatted LaTeX document with your answers, using the same (sub)section names as this document. Show your steps—your answers should contain complete proofs.

Due: Monday, April 17 at 11:59PM on GradeScope.

Problem 1: Exponential-gamma conjugacy

For this problem, use the following facts.

The exponential distribution with rate $\mu > 0$ has PDF

$$P(x \mid \mu) = \text{Expon}(x; \mu) = \mu \exp(-\mu x), \quad x > 0 \tag{1}$$

The gamma distribution with shape a > 0 and rate b > 0 has PDF

$$P(x \mid a, b) = \text{Gam}(x; a, b) = \frac{b^{a}}{\Gamma(a)} x^{a-1} \exp(-bx), \ x > 0$$
 (2)

In general, an exponential family distribution takes the following form:

$$P(x \mid \eta) = h(x) \exp\left(\eta^{\top} t(x) - a(\eta)\right) \tag{3}$$

where h(x) is the base measure, η are the natural parameters, t(x) are the sufficient statistics, and $a(\eta)$ is the log-normalizer.

A conjugate prior for η is also exponential family and takes the following form

$$P(\eta \mid \lambda) = h_c(\eta) \exp\left(\lambda_1^{\top} \eta - \lambda_0 a_{\ell}(\eta) - a_c(\lambda)\right) \tag{4}$$

where $\lambda = [\lambda_1, \lambda_0]$ are the natural parameters for the conjugate prior, $t(\eta) = [\eta, -a_\ell(\eta)]$ are its sufficient statistics, and $a_c(\lambda)$ is its log-normalizer. Note that $a_\ell(\eta)$ is the log-normalizer of the likelihood $P(x \mid \eta)$, while $a_c(\lambda)$ is the log-normalizer of the prior $P(\eta \mid \lambda)$.

1.1: Exponential family forms [10 points]

Provide exponential family forms for the exponential and gamma distributions. (This means defining h(x), t(x), η , and $a(\eta)$ and confirming that Eq. (3) equals the PDFs above.)

1.2: Conjugacy [10 points]

Use Eq. (4), to show that if the likelihood $P(x \mid \mu)$ is exponential (Eq. (1)), then the conjugate prior for μ is a gamma distribution $P(\mu \mid a, b)$ (Eq. (2)).

1.3: Posterior [10 points]

Provide the form of the gamma posterior $P(\mu \mid x_{1:n}, a, b)$ where $x_{1:n} \equiv x_1, \dots, x_n$, and $x_i \stackrel{\text{iid}}{\sim} P(x \mid \mu)$.

1.4: Prior predictive distribution [10 points]

Derive the prior predictive distribution $P(x_1 \mid a, b) = \int P(x_1 \mid \mu) P(\mu \mid a, b) d\mu$ for one data point x_1 .

1.5: Posterior predictive distribution [10 points]

Derive the posterior predictive distribution $P(x_{n+1} \mid x_{1:n}, a, b) = \int P(x_{n+1} \mid \mu) P(\mu \mid x_{1:n}, a, b) d\mu$ for a single new point x_{n+1} conditional on a data set $x_{1:n}$.

Problem 2: Gamma-Poisson and entropy

For this problem, use the following facts.

The Poisson distribution with rate $\mu > 0$ has PMF

$$P(x \mid \mu) = \operatorname{Pois}(x; \mu) = \frac{\mu^{x}}{x!} \exp(-\mu), \ x \in \mathbb{N}_{0}$$
 (5)

The negative binomial distribution with shape r > 0 and probability parameter $p \in (0, 1)$ has PMF

$$P(x \mid r, p) = NB(x; r, p) = \frac{\Gamma(x+r)}{x!\Gamma(r)} (1-p)^r p^x, \quad x \in \mathbb{N}_0$$
 (6)

A gamma-Poisson mixture is equal to a negative binomial

$$\int_0^\infty \operatorname{Pois}(x; \mu) \operatorname{Gam}(\mu; a, b) d\mu = \operatorname{NB}(x; a, \frac{1}{1+b})$$
 (7)

2.1: Posterior [5 points]

If $x \sim \text{Pois}(\mu)$ and $\mu \sim \text{Gam}(a, b)$, what is the posterior $P(\mu \mid x, a, b)$?

2.2: Exponential family forms [10 points]

Provide an exponential family form for the Poisson distribution.

In addition, provide an exponential family form for the negative binomial distribution with known r—this means only p is treated as a parameter, while r is treated as a known constant (e.g., like π or e).

2.3: KL divergence between two Poissons [10 points]

Use the exponential family form of the Poisson to derive the Kullback-Leibler (KL) divergence between two Poisson distributions, $\text{KL}(\text{Pois}(x;\mu_1)||\text{Pois}(x;\mu_2))$. Use the natural-log (ln) form of KL divergence: $\text{KL}(P(x)||Q(x)) = \sum_{x \in \mathcal{X}} P(x) \ln \left[\frac{P(x)}{Q(x)}\right]$.

2.4: Poisson and negative binomial entropies [25 points]

Define the following three quantities.

The entropy of a negative binomial distribution with shape a and probability parameter $\frac{1}{1+b}$:

$$H\left(NB(a, \frac{1}{1+b})\right) = -\sum_{x=0}^{\infty} NB(x; a, \frac{1}{1+b}) \ln\left[NB(x; a, \frac{1}{1+b})\right]$$
(8)

The entropy of a Poisson distribution with rate *y*:

$$H(\operatorname{Pois}(y)) = -\sum_{x=0}^{\infty} \operatorname{Pois}(x;y) \ln [\operatorname{Pois}(x;y)]$$
(9)

The conditional entropy of a Poisson, conditioned on a gamma prior over *y* with shape *a* and rate *b*:

$$H(\operatorname{Pois}(y) \mid \operatorname{Gam}(a,b)) = \int_0^\infty H(\operatorname{Pois}(y)) \operatorname{Gam}(y;a,b) \, dy \tag{10}$$

Show that the entropy of the negative binomial is lower bounded:

$$H\left(NB(a, \frac{1}{1+b})\right) \ge H\left(Pois(y) \mid Gam(a, b)\right).$$
 (11)