

Information Theory and Statistics

Lecture 5: Exponential families

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Ph. D. Programme 2013/2014

Parametric family

Definition (parametric family)

- A *parametric family of distributions* is a family of probability distributions indexed by parameter $\theta \in \Theta$, which specify probabilities of a stochastic process $(\mathbf{X}_i)_{i=-\infty}^{\infty}$.

- For discrete variables we write these distributions as

$$P(\mathbf{X}_1^n = \mathbf{x}_1^n | \theta).$$

- For real variables, we assume that there exists a probability density function $\rho(\mathbf{x}_1^n | \theta)$ which satisfies

$$P(\mathbf{X}_1^n \in \mathbf{A} | \theta) = \int_{\mathbf{A}} \rho(\mathbf{x}_1^n | \theta) d\mathbf{x}_1^n,$$

where $\int d\mathbf{x}_1^n$ is the integral with respect to the n -dimensional Lebesgue measure.

Random samples

- 1 Usually, parameter θ is a single real number or a vector.
- 2 It is also usually assumed that variables \mathbf{X}_i are probabilistically independent (given the parameter θ). In that case, we call \mathbf{X}_1^n a *random sample* of length n drawn from distribution $\mathbf{P}(\mathbf{X}_i = \mathbf{x}_i | \theta)$ or $\rho(\mathbf{x}_i | \theta)$, respectively. The first case will be called a *discrete random sample*, whereas the second will be called a *real random sample*.

Examples of parametric families

A random sample of length n drawn from Bernoulli distributions with success probability θ has probability distribution

$$P(\mathbf{X}_1^n = \mathbf{x}_1^n | \theta) = \prod_{i=1}^n \theta^{x_i} (1 - \theta)^{1-x_i},$$

where $x_i \in \{0, 1\}$ and $\theta \in (0, 1)$.

A random sample of length n drawn from normal (or Gauss) distributions with expectation μ and variance σ^2 has density

$$\rho(\mathbf{x}_1^n | \mu, \sigma) = \prod_{i=1}^n \frac{1}{\sigma\sqrt{2\pi}} \exp \left[-\frac{(x_i - \mu)^2}{2\sigma^2} \right],$$

where $x_i \in (-\infty, \infty)$, $\mu \in (-\infty, \infty)$, and $\sigma \in (0, \infty)$.

Discrete exponential families

Definition (exponential family (discrete))

Let function $\mathbf{p} : \mathbb{X} \rightarrow (0, \infty)$ satisfy $\sum_{\mathbf{x} \in \mathbb{X}} \mathbf{p}(\mathbf{x}) < \infty$. Having functions $\mathbf{T}_1 : \mathbb{X} \rightarrow \mathbb{R}$, we denote the canonical sum

$$\mathbf{Z}(\theta) = \sum_{\mathbf{x} \in \mathbb{X}} \mathbf{p}(\mathbf{x}) \exp \left(\sum_{l=1}^s \theta_l \mathbf{T}_l(\mathbf{x}) \right)$$

and define *s-parameter exponential family*

$$\mathbf{P}(\mathbf{X}_1^n = \mathbf{x}_1^n | \theta) = \prod_{i=1}^n \mathbf{p}(\mathbf{x}_i) \exp \left(\sum_{l=1}^s \theta_l \mathbf{T}_l(\mathbf{x}_i) - \ln \mathbf{Z}(\theta) \right)$$

for $\theta = (\theta_1, \theta_2, \dots, \theta_s) \in \Theta := \{\omega \in \mathbb{R}^s : \mathbf{Z}(\omega) < \infty\}$.

Bernoulli distributions as exponential family

Example

Bernoulli distributions form an exponential family because

$$\begin{aligned} P(\mathbf{X}_1^n = \mathbf{x}_1^n | \theta) &= \prod_{i=1}^n \theta^{x_i} (1 - \theta)^{1-x_i} \\ &= \prod_{i=1}^n \exp \left(x_i \ln \frac{\theta}{1 - \theta} + \ln(1 - \theta) \right) \\ &= \prod_{i=1}^n \exp (\eta x_i - \ln Z(\eta)), \end{aligned}$$

where $\eta = \ln \frac{\theta}{1 - \theta}$ and $Z(\eta) = 1 - \theta$. Function $\eta = \eta(\theta)$ is called the logit function.

Real exponential families

Definition (exponential family (real))

Let function $\mathbf{p} : \mathbb{R} \rightarrow (0, \infty)$ satisfy $\int \mathbf{p}(\mathbf{x})d\mathbf{x} < \infty$. Having functions $\mathbf{T}_1 : \mathbb{X} \rightarrow \mathbb{R}$, we denote the canonical sum

$$\mathbf{Z}(\boldsymbol{\theta}) = \int \mathbf{p}(\mathbf{x}) \exp \left(\sum_{l=1}^s \theta_l \mathbf{T}_l(\mathbf{x}) \right) d\mathbf{x}$$

and define *s-parameter exponential family*

$$\rho(\mathbf{x}_1^n | \boldsymbol{\theta}) = \prod_{i=1}^n \mathbf{p}(\mathbf{x}_i) \exp \left(\sum_{l=1}^s \theta_l \mathbf{T}_l(\mathbf{x}_i) - \ln \mathbf{Z}(\boldsymbol{\theta}) \right)$$

for $\boldsymbol{\theta} = (\theta_1, \theta_2, \dots, \theta_s) \in \Theta := \{\boldsymbol{\theta}' \in \mathbb{R}^s : \mathbf{Z}(\boldsymbol{\theta}') < \infty\}$. The *s-parameter exponential family* is called of *full rank* if the interior of Θ is not empty and \mathbf{T}_1 do not satisfy a linear constraint of the form $\sum_{i=1}^s \mathbf{a}_i \mathbf{T}_1(\mathbf{x}_i) = \mathbf{c}$ for a constant \mathbf{c} .

Normal distributions as exponential family

Example

Normal distributions form an exponential family because

$$\begin{aligned}\rho(\mathbf{x}_1^n | \mu, \sigma) &= \prod_{i=1}^n \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{(x_i - \mu)^2}{2\sigma^2}\right] \\ &= \prod_{i=1}^n \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{x_i^2}{2\sigma^2} + \frac{\mu x_i}{\sigma^2} - \frac{\mu^2}{2\sigma^2}\right] \\ &= \prod_{i=1}^n \exp\left(\alpha x_i^2 + \beta x_i - \ln Z(\alpha, \beta)\right),\end{aligned}$$

where $\alpha = -\frac{1}{2\sigma^2}$, $\beta = \frac{\mu}{\sigma^2}$, and $Z(\alpha, \beta) = \sigma\sqrt{2\pi} \exp\left[\frac{\mu^2}{2\sigma^2}\right]$.

The problem of maximum entropy

The problem of maximum entropy modeling is:

Problem (maximum entropy)

Find the probability density ρ that maximizes entropy

$$H(\rho) = - \int \rho(x) \ln \rho(x) dx \quad (1)$$

given constraints:

$$\int \rho(x) dx = 1, \quad (2)$$

$$\int \rho(x) T_i(x) dx = \alpha_i, \quad 1 \leq i \leq m. \quad (3)$$

Similar problems of maximizing entropy given some constraints appear in many applications, in machine learning in particular.

The solution of maximum entropy

Theorem

If there exists density

$$\rho^*(\mathbf{x}) = \exp \left[\lambda_0^* + \sum_{i=1}^m \lambda_i^* T_i(\mathbf{x}) \right], \quad (4)$$

where λ_i^ are chosen so that ρ^* satisfies conditions (2)–(3), then ρ^* maximizes entropy (1) on the space of probability densities that satisfy (2)–(3).*

Some remarks

- 1 The solution of the maximum entropy problem for discrete distributions is analogous, with probabilities replacing probability densities.
- 2 In certain maximization problems, there exists no ρ^* that satisfies (2)–(3). In such cases there is no distribution having the maximal entropy. This happens for example for constraints $\int \mathbf{x}^k \rho(\mathbf{x}) d\mathbf{x} = \alpha_k$, where $\mathbf{k} = \mathbf{0}, \mathbf{1}, \mathbf{2}, \mathbf{3}$. In that case we would obtain

$$\rho(\mathbf{x}) = \exp \left[\lambda_0 + \lambda_1 \mathbf{x} + \lambda_2 \mathbf{x}^2 + \lambda_3 \mathbf{x}^3 \right],$$

which cannot be normalized for any $\lambda_3 \neq \mathbf{0}$ because $\rho(\mathbf{x})$ tends to infinity for either for $\mathbf{x} \rightarrow \infty$ or $\mathbf{x} \rightarrow -\infty$.

Proof

Let ρ satisfy constraints (2)–(3). We obtain

$$\begin{aligned} \mathbf{H}(\rho) &= - \int \rho(\mathbf{x}) \ln \rho(\mathbf{x}) d\mathbf{x} \\ &= -\mathbf{D}(\rho \parallel \rho^*) - \int \rho(\mathbf{x}) \ln \rho^*(\mathbf{x}) d\mathbf{x} \\ &\leq - \int \rho(\mathbf{x}) \ln \rho^*(\mathbf{x}) d\mathbf{x} \\ &= - \int \rho(\mathbf{x}) \left[\lambda_0^* + \sum_{i=1}^m \lambda_i^* \mathbf{T}_i(\mathbf{x}) \right] d\mathbf{x} \\ &= - \int \rho^*(\mathbf{x}) \left[\lambda_0^* + \sum_{i=1}^m \lambda_i^* \mathbf{T}_i(\mathbf{x}) \right] d\mathbf{x} \\ &= - \int \rho^*(\mathbf{x}) \ln \rho^*(\mathbf{x}) d\mathbf{x} = \mathbf{H}(\rho^*), \end{aligned}$$

with the equality if and only if ρ and ρ^* are equal.

Langrangian function

The remaining problem is to find the suitable λ_i^* .

Theorem

Consider the density ρ_λ and the Lagrangian function $\mathbf{L}(\lambda)$ defined

$$\rho_\lambda(\mathbf{x}) = \exp \left[\sum_{i=1}^m \lambda_i T_i(\mathbf{x}) - \ln Z(\lambda) \right], \quad (5)$$

$$\mathbf{L}(\lambda) = \ln Z(\lambda) - \sum_{i=1}^k \lambda_i \alpha_i, \quad (6)$$

where the canonical sum $Z(\lambda) = \int \exp \left[\sum_{i=1}^m \lambda_i T_i(\mathbf{x}) \right] d\mathbf{x}$.

Function $\mathbf{L}(\lambda)$ has a single minimum and $\lambda^* = (\lambda_1^*, \dots, \lambda_m^*)$ for which (5) satisfies conditions (3) is the solution of

$$\lambda^* = \arg \min_{\lambda} \mathbf{L}(\lambda). \quad (7)$$

Proof

We have

$$\begin{aligned}\frac{\partial \mathbf{L}(\lambda)}{\partial \lambda_j} &= \frac{1}{\mathbf{Z}(\lambda)} \int \mathbf{T}_j(\mathbf{x}) \exp \left[\sum_{i=1}^m \lambda_i \mathbf{T}_i(\mathbf{x}) \right] d\mathbf{x} - \alpha_j \\ &= \int \rho_\lambda(\mathbf{x}) \mathbf{T}_j(\mathbf{x}) d\mathbf{x} - \alpha_j.\end{aligned}$$

Hence the Lagrangian has an extremum if and only if ρ_λ satisfies conditions (3). Further analysis shows that there is only one extremum and it is a minimum because the Lagrangian is convex.

Proof (continued)

Indeed we obtain

$$\begin{aligned} \frac{\partial^2 \mathbf{L}(\boldsymbol{\lambda})}{\partial \lambda_j \partial \lambda_k} &= \frac{\partial}{\partial \lambda_k} \left[\frac{1}{\mathbf{Z}(\boldsymbol{\lambda})} \int \mathbf{T}_j(\mathbf{x}) \exp \left[\sum_{i=1}^m \lambda_i \mathbf{T}_i(\mathbf{x}) \right] d\mathbf{x} \right] \\ &= -\frac{1}{[\mathbf{Z}(\boldsymbol{\lambda})]^2} \left[\int \mathbf{T}_k(\mathbf{x}) \exp \left[\sum_{i=1}^m \lambda_i \mathbf{T}_i(\mathbf{x}) \right] d\mathbf{x} \right] \\ &\quad \times \left[\int \mathbf{T}_j(\mathbf{x}) \exp \left[\sum_{i=1}^m \lambda_i \mathbf{T}_i(\mathbf{x}) \right] d\mathbf{x} \right] \\ &\quad + \frac{1}{\mathbf{Z}(\boldsymbol{\lambda})} \int \mathbf{T}_k(\mathbf{x}) \mathbf{T}_j(\mathbf{x}) \exp \left[\sum_{i=1}^m \lambda_i \mathbf{T}_i(\mathbf{x}) \right] d\mathbf{x}. \end{aligned}$$

Writing $\mathbf{E} \mathbf{T} = \int \rho_{\boldsymbol{\lambda}}(\mathbf{x}) \mathbf{T}(\mathbf{x}) d\mathbf{x}$, we have

$$\frac{\partial^2 \mathbf{L}(\boldsymbol{\lambda})}{\partial \lambda_j \partial \lambda_k} = \mathbf{E} (\mathbf{T}_j \mathbf{T}_k) - \mathbf{E} \mathbf{T}_j \mathbf{E} \mathbf{T}_k = \mathbf{E} [\mathbf{T}_j - \mathbf{E} \mathbf{T}_j] [\mathbf{T}_k - \mathbf{E} \mathbf{T}_k].$$

Proof (finished)

We observe that the second derivative of the Lagrangian is a covariance matrix, which is nonnegative definite, i.e.,

$$\sum_{j,k=1}^m a_j \frac{\partial^2 L(\lambda)}{\partial \lambda_j \partial \lambda_k} a_k = \mathbf{E} \left[\sum_{j=1}^m a_j [T_j - \mathbf{E} T_j] \right]^2 \geq \mathbf{0}.$$

Hence the Lagrangian is convex and there is only one extremum.

Recapitulation

- Coefficients λ_i^* can be found by minimizing Lagrangian $L(\lambda)$.
- In many problems of machine learning this can be only done numerically.
- The suitable minimization can be performed using generic minimization algorithms, e.g. minimization by conjugate gradients, or algorithms dedicated for the Lagrangian, e.g. the iterative scaling.

Improved iterative scaling

Let us assume that

$$\mathbf{T}_i(\mathbf{x}) \geq \mathbf{0}.$$

Then we can minimize Lagrangian $\mathbf{L}(\boldsymbol{\lambda})$ via the improved iterative scaling.

Let $\boldsymbol{\delta} = (\delta_1, \dots, \delta_m)$. By inequality $\log \mathbf{y} \leq \mathbf{y} - \mathbf{1}$ we have

$$\begin{aligned} \mathbf{L}(\boldsymbol{\lambda} + \boldsymbol{\delta}) - \mathbf{L}(\boldsymbol{\lambda}) &\leq \mathbf{A}(\boldsymbol{\lambda}, \boldsymbol{\delta}) := \frac{\mathbf{Z}(\boldsymbol{\lambda} + \boldsymbol{\delta})}{\mathbf{Z}(\boldsymbol{\lambda})} - \mathbf{1} - \sum_{i=1}^m \delta_i \alpha_i \\ &= \int \rho_{\boldsymbol{\lambda}}(\mathbf{x}) \exp \left[\sum_{i=1}^m \delta_i \mathbf{T}_i(\mathbf{x}) \right] - \mathbf{1} - \sum_{i=1}^m \delta_i \alpha_i d\mathbf{x}. \end{aligned}$$

Improved iterative scaling (continued)

Function $\mathbf{y} \mapsto \exp \mathbf{y}$ is convex, hence $\exp \left[\sum_{i=1}^m \mathbf{n}_i \mathbf{g}_i \right] \leq \sum_{i=1}^m \mathbf{n}_i \exp \mathbf{g}_i$ for $\mathbf{n}_i \geq \mathbf{0}$, $\sum_{i=1}^m \mathbf{n}_i = \mathbf{1}$ by the Jensen inequality. Then putting $\mathbf{T}_+(\mathbf{x}) = \sum_{i=1}^m \mathbf{T}_i(\mathbf{x})$ and setting $\mathbf{n}_i = \mathbf{T}_i(\mathbf{x})/\mathbf{T}_+(\mathbf{x})$ and $\mathbf{g}_i = \delta_i \mathbf{T}_+(\mathbf{x})$ we obtain

$$\mathbf{A}(\lambda, \delta) \leq \mathbf{B}(\lambda, \delta) := \int \rho_\lambda(\mathbf{x}) \sum_{i=1}^m \frac{\mathbf{T}_i(\mathbf{x})}{\mathbf{T}_+(\mathbf{x})} \exp [\delta_i \mathbf{T}_+(\mathbf{x})] \mathbf{d}\mathbf{x} - \mathbf{1} - \sum_{i=1}^m \delta_i \alpha_i.$$

The derivatives of $\mathbf{B}(\lambda, \delta)$ w.r.t δ are

$$\frac{\partial \mathbf{B}(\lambda, \delta)}{\partial \delta_i} = \mathbf{B}'(\lambda, \delta_i) := \int \rho_\lambda(\mathbf{x}) \mathbf{T}_i(\mathbf{x}) \exp [\delta_i \mathbf{T}_+(\mathbf{x})] \mathbf{d}\mathbf{x} - \alpha_i,$$
$$\frac{\partial^2 \mathbf{B}(\lambda, \delta)}{\partial \delta_i^2} = \mathbf{B}''(\lambda, \delta_i) := \int \rho_\lambda(\mathbf{x}) \mathbf{T}_i(\mathbf{x}) \mathbf{T}_+(\mathbf{x}) \exp [\delta_i \mathbf{T}_+(\mathbf{x})] \mathbf{d}\mathbf{x}.$$

In the improved iterative scaling algorithm, we approximate finding the minimum of $\mathbf{L}(\lambda)$ via stepwise finding of the minima of $\mathbf{B}(\lambda, \delta)$ using the Newton's method.

Improved iterative scaling (continued)

The minimum of $\mathbf{B}(\boldsymbol{\lambda}, \boldsymbol{\delta})$ corresponds to condition

$$\mathbf{B}'(\boldsymbol{\lambda}, \delta_i) = 0$$

for all i . In the Newton's method, the zero of the derivative of $\mathbf{B}'(\boldsymbol{\lambda}, \delta_i)$ can be found by iteration

$$\delta_i \leftarrow \delta_i - \frac{\mathbf{B}'(\boldsymbol{\lambda}, \delta_i)}{\mathbf{B}''(\boldsymbol{\lambda}, \delta_i)}$$

until sufficient convergence is observed.

Improved iterative scaling (finished)

procedure IMPROVED ITERATIVE SCALING

for $i \in \{1, \dots, k\}$ **do**

$\lambda_i \leftarrow 0$

end for

repeat

for $i \in \{1, \dots, k\}$ **do**

$\delta_i \leftarrow 1$

while $\left| \frac{B'(\lambda, \delta_i)}{B''(\lambda, \delta_i)} \right| > \epsilon$ **do**

$\delta_i \leftarrow \delta_i - \frac{B'(\lambda, \delta_i)}{B''(\lambda, \delta_i)}$

end while

$\lambda_i \leftarrow \lambda_i + \delta_i$

end for

until $\max_{i \in \{1, \dots, k\}} |\delta_i| > \epsilon$

for $i \in \{1, \dots, k\}$ **do**

return λ_i

end for

end procedure