## **Probabilistic Machine Learning**

Tutorial 2

Start: 10.15

Keep your solution open in the background

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### Tutorials over Zoom

quick reminde

**New:** Co-tutor present to assist tutor (chat etc.)

Communication & interaction within the zoom tutorial (controlled by tutors)

**+ Speak:** Participants → raise hand → unmute

#### **Exercise submissions**

- + Stick to the naming scheme, please: 02\_<YourSurname>\_<YourMatrikelnummer>.pdf
- + Make sure figures are visible in your submission

### Shifting the tutorial?

+ There will be a poll: Monday vs. Thursday



#### Given:

N binary observations  $X:=[x_1,\ldots,x_N]$  iid. from Bernoulli distribution (likelihood of f)

$$p(x_i | f) = f^{x_i} \cdot (1 - f)^{1 - x_i}$$
 for  $i = 1, ..., N$ 

Beta prior on f

$$p(f\,|\,a,b) = \mathcal{B}(f;a,b) := \frac{1}{B(a,b)} f^{\,a-1} \cdot (1-f)^{b-1} \qquad \text{with } a,b>0, \quad f \in [0,1].$$

**Question:** What is the posterior p(f | X)?

### Side note on the likelihood:

Never say "the likelihood of the data". Always say "the likelihood of the parameters". The likelihood function is not a probability distribution [in the parameters]. (David J. C. MacKay: Information Theory, Inference, and Learning Algorithms)

$$p(x_i | f) = f^{x_i} \cdot (1 - f)^{1 - x_i}$$

(L)

$$p(f | a, b) \propto f^{a-1} \cdot (1-f)^{b-1}$$
 (P)

$$p(f \mid X) = \frac{p(X \mid f)p(f)}{p(X)} \propto p(X \mid f)p(f)$$

$$\stackrel{\text{iid.}}{=} p(f) \prod_{i=1}^{N} p(x_i \mid f)$$

$$\propto f^{a-1} \cdot (1-f)^{b-1} \prod_{i=1}^{N} f^{x_i} \cdot (1-f)^{1-x_i}$$

$$= f^{a-1} (1-f)^{b-1} \cdot f^{\sum_{i=1}^{N} x_i} (1-f)^{\sum_{i=1}^{N} 1-x_i}$$

$$= f^{a+\sum_{i=1}^{N} x_i-1} (1-f)^{b+N-\sum_{i=1}^{N} x_i-1}$$

$$= f^{\tilde{a}-1} (1-f)^{\tilde{b}-1}$$

$$\propto \mathcal{B}(f; \tilde{a}, \tilde{b})$$

Bayes' theorem

plug in (L),(P)

,

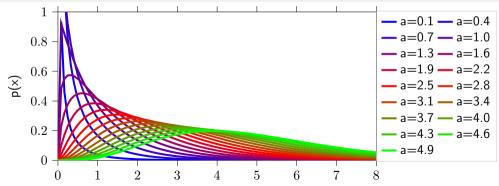


The Gamma distribution

**Task:** Given  $X \sim \mathcal{G}(a,1)$  and  $Y \sim \mathcal{G}(b,1)$ , show that  $Z = \frac{X}{X+Y} \sim \mathcal{B}(a,b)$ 

$$\mathcal{G}(\xi; \alpha, \beta) = \frac{\beta^{\alpha} \cdot \xi^{\alpha - 1} e^{-\beta \xi}}{\Gamma(\alpha)}$$

**Watch out:** Two definitions of the Gamma distribution out there:  $\beta = \frac{1}{\theta}$  (cf. lecture 4, slide 15)



**Task:** Given  $X \sim \mathcal{G}(a,1)$  and  $Y \sim \mathcal{G}(b,1)$ , show that  $Z = \frac{X}{X+Y} \sim \mathcal{B}(a,b)$ 

#### Reminder from lecture:

## Theorem (Transformation Law, general)

Let  $X=(X_1,\ldots,X_d)$  have a joint density  $p_X$ . Let  $g:\mathbb{R}^d\to\mathbb{R}^d$  be continously differentiable and injective, with non-vanishing Jacobian  $J_g$ . Then Y=g(X) has density

$$p_Y(y) = \begin{cases} p_X(g^{-1}(y)) \cdot |J_{g^{-1}}(y)| & \text{if } y \text{ is in the range of } g, \\ 0 & \text{otherwise.} \end{cases}$$

$$g(x,y)=rac{x}{x+y}$$
 maps from  $\mathbb{R}^2_+\mapsto [0,1]$ , so we need a dummy variable to avoid a singular Jacobian, e.g.  $g(x,y)=\left(x,rac{x}{x+y}
ight)$  for  $x
eq 0$ , or  $g(x,y)=\left(x+y,rac{x}{x+y}
ight)$ 

**Solution:** The function  $g: \mathbb{R}^2_+ \mapsto \mathbb{R}_+ \times [0,1]$  as

$$g(x,y) = \left(x+y, \frac{x}{x+y}\right)$$

is injective. Thus, define the auxiliary variable W=X+Y. Then X=ZW and Y=W-ZW.

### Approach:

- 1. Find transformation  $p_{X,Y}(x,y) \to p_{W,Z}(w,z)$
- 2. Marginalize  $p_Z(z) = \int p_{W,Z}(w,z) dw$

First, compute Jacobian for the transform  $p_{X,Y}(x,y) o p_{W,Z}(w,z)$ 

$$\left| \frac{dg^{-1}(z,w)}{d(z,w)} \right| = \left| \frac{\frac{dz}{dz}}{\frac{dy}{dz}} - \frac{\frac{dx}{dw}}{\frac{dy}{dw}} \right| = \left| w \quad z \\ -w \quad 1-z \right| = w(1-z) + wz = w$$

**Memo:** 
$$X = ZW$$
 and  $Y = W - ZW$ ; with Jacobian  $\left| \frac{dg^{-1}(z,w)}{d(z,w)} \right| = w$ 

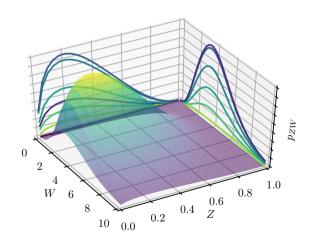
Next, compute the joint over Z and W is

$$\begin{aligned} p_{Z,W}(z,w) &= p_{X,Y}(x(z,w),y(z,w)) \cdot \left| \frac{dg^{-1}(z,w)}{d(z,w)} \right| \\ &= p_X(x(z,w)) \ p_Y(y(z,w)) \cdot w \\ &= \mathcal{G}(zw;a,1) \ \mathcal{G}(w-zw;b,1) \cdot w \\ &= \frac{1}{\Gamma(a)\Gamma(b)} (zw)^{a-1} e^{-zw} (w-zw)^{b-1} e^{-w+zw} w \\ &= \frac{1}{\Gamma(a)\Gamma(b)} w^{a+b-1} z^{a-1} (1-z)^{b-1} e^{-w} \\ &= p_Z(z) p_W(w) \end{aligned}$$

Joint over  ${\cal Z}$  and  ${\cal W}$  visualized

$$p_{Z,W}(z, w) = p_{Z}(z)p_{W}(w)$$

$$\propto z^{a-1}(1-z)^{b-1}w^{a+b-1}e^{-w}$$



Marginalize over W

$$p_{Z}(z) = \int_{0}^{\infty} dw \ p_{Z,W}(z,w)$$

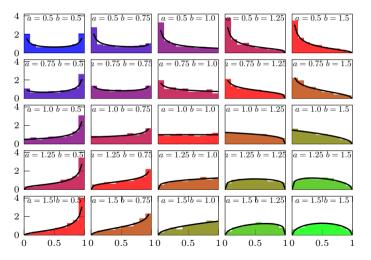
$$= \frac{1}{\Gamma(a)\Gamma(b)} z^{a-1} (1-z)^{b-1} \int_{0}^{\infty} dw \ \underbrace{w^{a+b-1}e^{-w}}_{\propto \mathcal{G}(w;a+b,1)}$$

$$= \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} z^{a-1} (1-z)^{b-1}$$

$$= \frac{1}{B(a,b)} z^{a-1} (1-z)^{b-1}$$

$$= \mathcal{B}(z;a,b)$$

A Python example



$$X \sim \mathcal{G}(a, 1); \quad Y \sim \mathcal{G}(b, 1)$$
  

$$\Rightarrow Z = \frac{X}{X + Y} \sim \mathcal{B}(a, b)$$

import numpy as np
from scipy.stats import gamma

```
n_param = 5
N = 1000
a = np.linspace(0.5, 1.5, n_param)
b = np.linspace(0.5, 1.5, n_param)
```

```
for i in range(n_param):
    for j in range(n_param):
        x = gamma.rvs(a[i], size=N)
        y = gamma.rvs(b[j], size=N)
        z = x/(x+y)
```

# Theory Question: (b) Mean of the Beta distribution

$$\begin{split} \mathbb{E}_{\mathcal{B}(z;a,b)}[z] &= \int_0^1 z \; \mathcal{B}(z;a,b) \; dz \\ &= \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \underbrace{\int_0^1 z^a (1-z)^{b-1} \; dz}_{=B(a+1,b)} \\ &= \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \frac{\Gamma(a+1)\Gamma(b)}{\Gamma(a+b+1)} \quad \text{using } B(a+1,b) = \frac{\Gamma(a+1)\Gamma(b)}{\Gamma(a+b+1)} \\ &= \frac{\Gamma(a+b)}{\Gamma(a)} \cdot \frac{a\Gamma(a)}{(a+b)\Gamma(a+b)} \quad \text{using } \Gamma(x+1) = x\Gamma(x) \\ &= \frac{a}{a+b} \end{split}$$

