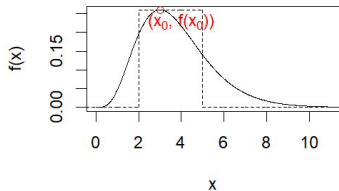


# Algorithms and Data Structures

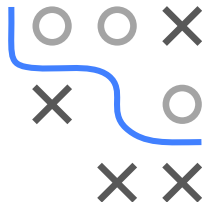
## Quadrature

## Laplace's method



### Learning goals

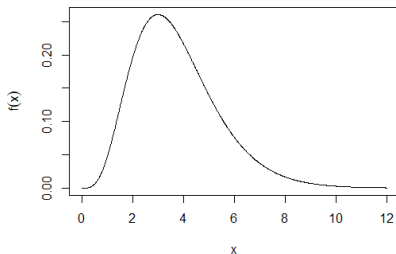
- Laplace's method



# LAPLACE'S METHOD

**Target:** Approximate integral of function  $f$  with the following properties:

- The mass concentrates on a small area around a center and the function has very rapidly decreasing tails ("similarity" to the density of a normal distribution)
- The function we want to integrate is the density of a random variable that is approximately normally distributed



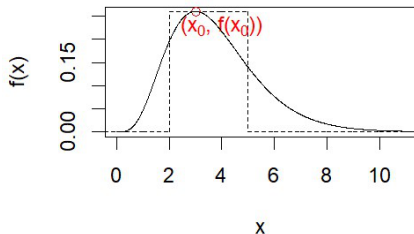
# LAPLACE'S METHOD / 2

In particular, we assume that  $f$

- Can only be positive
- Is two times continuously differentiable
- Has a **global maximum** at  $x_0$

We could approximate the area underneath the graph of the function with a staircase function and represent the integral with a very simple formula that depends on  $f(x_0)$ :

$$\int f(x) dx \approx f(x_0) \cdot c$$

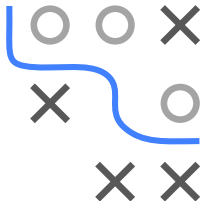


# LAPLACE'S METHOD / 3

But instead of the step function we would like to choose a function that approximates  $f$  **better** and which has well-known properties.

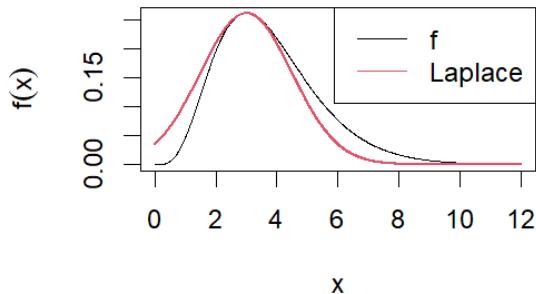
**Idea:** Approximate the integral using the density function of the normal distribution!

**How?** We center and scale the density function of the normal distribution such that it approximates  $f$  "best possible".



# LAPLACE'S METHOD / 4

In other words: We determine **expectation** and **standard deviation** of a normal distribution such that the corresponding density function fits best possible to the function  $f$  we are interested in.



# LAPLACE'S METHOD / 5

## Mathematical derivation:

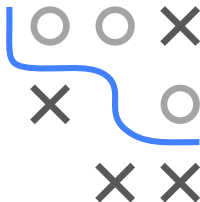
Let there be a function  $f$  with a global maximum at  $x_0$ .

We define  $h(x) := \log f(x)$  as the logarithmized function and rewrite the integral

$$\int_a^b f(x) dx = \int_a^b \exp(\underbrace{\log f(x)}_{:=h(x)}) dx$$

Using Taylor's theorem around  $x_0$  we obtain

$$\int_a^b \exp(h(x)) \approx \int_a^b \exp\left(h(x_0) + h'(x_0)(x - x_0) + \frac{1}{2}h''(x_0)(x - x_0)^2\right) dx$$



# LAPLACE'S METHOD / 6

$x_0$  is also the maximum of  $h(x) = \log(f(x))$ . Hence,  $h'(x_0) = 0$  and the second summand disappears:

$$\int_a^b \exp(h(x)) \, dx \approx \int_a^b \exp\left(h(x_0) + \frac{1}{2}h''(x_0)(x - x_0)^2\right) \, dx$$

We take advantage of the fact that  $\exp(x + y) = \exp(x) \exp(y)$

$$\int_a^b \exp(h(x_0)) \cdot \exp\left(\frac{1}{2}h''(x_0)(x - x_0)^2\right) \, dx$$

and pull the constant  $\exp(h(x_0))$  out of the integral

$$\exp(h(x_0)) \cdot \int_a^b \exp\left(\frac{1}{2}h''(x_0)(x - x_0)^2\right) \, dx$$



# LAPLACE'S METHOD / 7

Within the integral there is now an expression which "almost" corresponds to the density of a normal distribution with expectation  $\mu := x_0$  and variance  $\sigma^2 := -h''(x_0)^{-1}$ :

$$\begin{aligned}\int_a^b f(x) dx &\approx \exp(h(x_0)) \cdot \int_a^b \exp\left(\frac{1}{2}h''(x_0)(x - x_0)^2\right) dx \\ &= \exp(h(x_0)) \cdot \int_a^b \exp\left(-\frac{1}{2} \frac{(x - x_0)^2}{-h''(x_0)^{-1}}\right) dx \\ &= \exp(h(x_0)) \cdot \int_a^b \exp\left(-\frac{1}{2} \frac{(x - \mu)^2}{\sigma^2}\right) dx\end{aligned}$$

$-h''(x_0)^{-1}$  must be truly positive to correspond to the variance of a normal distribution. Since  $h(x)$  has a global maximum in  $x_0$ , the second derivative at this point is negative and therefore  $-h''(x_0)^{-1} > 0$ .





# LAPLACE'S METHOD / 8

If we add (and cancel) the multiplicative constant  $c = \frac{1}{\sqrt{2\pi\sigma^2}}$ , we obtain

$$\begin{aligned}\int_a^b f(x) dx &\approx \frac{1}{c} \cdot \exp(h(x_0)) \cdot \underbrace{\int_a^b c \cdot \exp\left(-\frac{1}{2} \frac{(x - \mu)^2}{\sigma^2}\right) dx}_{\text{Density ND}} \\&= \frac{1}{c} \underbrace{\exp(h(x_0))}_{f(x_0)} \cdot \int_a^b \phi_{\mu, \sigma^2}(x) dx \\&= \frac{1}{c} f(x_0) \cdot (\Phi_{\mu, \sigma^2}(b) - \Phi_{\mu, \sigma^2}(a))\end{aligned}$$

where  $\phi_{\mu, \sigma^2}(x)$  denotes the density and  $\Phi_{\mu, \sigma^2}(x)$  the distribution function of a normal distribution with expectation  $\mu$  and variance  $\sigma^2$ .



# LAPLACE'S METHOD / 9

For integration limits  $b = \infty$  and  $a = -\infty$  Laplace's method of  $f$  is then

$$\begin{aligned}\int_{-\infty}^{\infty} f(x) dx &\approx \frac{1}{c} \cdot f(x_0) \cdot (\Phi_{\mu, \sigma^2}(+\infty) - \Phi_{\mu, \sigma^2}(-\infty)) \\ &= \sqrt{-\frac{2\pi}{h''(x_0)}} \cdot f(x_0)\end{aligned}$$

with  $h(x) = \log f(x)$ .

Laplace's method thus corresponds to a value that only depends on the maximum of the function  $f(x_0)$  and the curvature of the logarithmic function  $h''(x_0)$ .



# LAPLACE'S METHOD / 10

Laplace's method also works well in higher dimensions. For  $f : \mathbb{R}^m \rightarrow \mathbb{R}$  with global maximum in  $\mathbf{x}_0$  the generalized form is given by

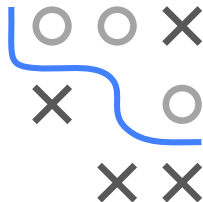
$$I(f) \approx (2\pi)^{m/2} \det(-H_f(\mathbf{x}_0)^{-1})^{1/2} \exp(f(\mathbf{x}_0))$$

where  $H_f(\mathbf{x}_0)$  denotes the Hessian matrix of  $f$  at  $\mathbf{x}_0$ . Since  $\mathbf{x}_0$  is a global maximum,  $H_f(\mathbf{x}_0)$  is negative definite.

The problem of integration is reduced to

- Solving an optimization problem  $\rightarrow$  find  $\mathbf{x}_0$
- Determining the second derivative  $h''(x)$  (or generally the Hessian matrix  $H_f(\mathbf{x})$ ) at the optimal position  $\mathbf{x}_0$ .

Instead of integration, an optimization problem must now be solved, which is often much easier and faster.



# LAPLACE'S METHOD: EXAMPLE

**Application example:** Bayesian computation

**Given:**

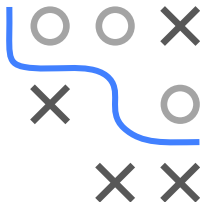
$$\begin{aligned}x|\lambda &\sim \text{Poisson}(\lambda) \quad (\text{Likelihood}) \\ \lambda &\sim \text{Gamma}(\alpha, \beta) \quad (\text{Prior})\end{aligned}$$

**Wanted:** Posterior density of the parameter  $\lambda$  given  $n$  observations

$$\mathbf{x} = (x^{(1)}, x^{(2)}, \dots, x^{(n)})$$

$$p(\lambda|\mathbf{x}) = \frac{\overset{\text{Likelihood}}{p(\mathbf{x}|\lambda)} \cdot \overset{\text{Prior}}{\pi(\lambda)}}{\int p(\mathbf{x}|\lambda) \cdot \pi(\lambda) d\lambda}$$

The density of the gamma distribution is given by  $\pi_{\alpha, \beta}(\lambda) = \frac{1}{\beta^\alpha \Gamma(\alpha)} \lambda^{\alpha-1} \exp(-\lambda\beta)$



# LAPLACE'S METHOD: EXAMPLE / 2

To keep the calculations simple, we calculate the posterior density for only **one** observation  $x$ .

The posterior density of  $\lambda$  given the observation  $x$  is (except for one constant)

$$p(\lambda|x) \propto \lambda^{x+\alpha-1} \exp\left(-\frac{\lambda}{1/\beta+1}\right) =: f(\lambda).$$

So to determine the posterior density  $p(\lambda|x)$  **exactly**, we search for the normalization constant  $c$ , which ensures that  $\int c \cdot f(\lambda) d\lambda = 1$ , hence

$$\begin{aligned} c \cdot \int f(\lambda) d\lambda &= 1 \\ c &= \frac{1}{\int f(\lambda) d\lambda} \end{aligned}$$



# LAPLACE'S METHOD: EXAMPLE / 3

**Goal:** Approximation of  $\int f(\lambda) d\lambda$  with  $f(\lambda) = \lambda^{x+\alpha-1} \exp\left(-\frac{\lambda}{1/\beta+1}\right)$

We calculate  $h(\lambda) = \log f(\lambda)$

$$h(\lambda) = \log\left(\lambda^{x+\alpha-1} \cdot \exp\left(-\frac{\lambda}{1/\beta+1}\right)\right)$$

$$= (x + \alpha - 1) \log \lambda - \frac{\lambda}{1/\beta + 1}$$

$$h'(\lambda) = \frac{x + \alpha - 1}{\lambda} - \frac{1}{1/\beta + 1}$$

$$h''(\lambda) = -\frac{x + \alpha - 1}{\lambda^2}$$



# LAPLACE'S METHOD: EXAMPLE / 4

To approximate the integral using Laplace's method, we need  $\lambda_0 := \arg \max f(\lambda)$  and  $h''(\lambda_0)$ , where  $h(\lambda) := \log(f(\lambda))$ .

The maximum of  $f(\lambda)$  is the same as the maximum of  $h(\lambda)$  (easier to calculate)

$$\begin{aligned} h'(\lambda) &= 0 \\ \frac{x + \alpha - 1}{\lambda} - \frac{1}{1/\beta + 1} &= 0 \\ \lambda_0 &= \frac{x + \alpha - 1}{1/\beta + 1} \end{aligned}$$

and thus

$$h''(\lambda_0) = -\frac{(1/\beta + 1)^2}{x + \alpha - 1}$$



# LAPLACE'S METHOD: EXAMPLE / 5

We insert  $\lambda_0 = \frac{x+\alpha-1}{1/\beta+1}$  and  $h''(\lambda_0)$  into the formula for Laplace's method and obtain

$$\begin{aligned}\int f(\lambda) d\lambda &\approx \sqrt{-\frac{2\pi}{h''(\lambda_0)}} \cdot f(\lambda_0) \\ &= \sqrt{2\pi} \cdot \frac{\sqrt{x+\alpha-1}}{1/\beta+1} \cdot f(\lambda_0)\end{aligned}$$

Hence, the normalization constant  $c$  can be approximated by

$$c = \frac{1}{\int f(\lambda) d\lambda} \approx \frac{1}{\sqrt{2\pi}} \frac{1/\beta+1}{\sqrt{x+\alpha-1}} \cdot \frac{1}{f(\lambda_0)}$$





# LAPLACE'S METHOD: EXAMPLE / 6

When calculating posterior distributions, Laplace's method provides a good approximation if

- The number  $n$  of observations is large
- The posterior distributions are roughly symmetric

