

## Normal - Normal

Given :  $x_i | \mu \sim N(\mu, \sigma^2)$  i.i.d

$\mu \sim N(\beta, \tau^2)$  (prior)

Then :  $\mu | x_1, \dots, x_n = \mu | \bar{x} \sim N\left(\frac{\beta \sigma^2/n + \bar{x} \tau^2}{\sigma^2/n + \tau^2}, \frac{\tau^2 \sigma^2/n}{\sigma^2/n + \tau^2}\right)$

where  $\bar{x} = \sum_{i=1}^n x_i / n$  (average)

posterior for  $\mu$

Conjugate prior

## Application to a classical problem

mean of  
two groups

Given:  $x_i | \mu_x \sim N(\mu_x, \sigma_x^2)$  n i.i.d samples

$y_i | \mu_y \sim N(\mu_y, \sigma_y^2)$  m i.i.d samples

Decide if  $\mu_x = \mu_y$ . Classical approach: Construct  $z = \frac{\bar{x} - \bar{y}}{\sqrt{\sigma_x^2/n + \sigma_y^2/m}}$

What do we know?

$$\bar{x} \sim N(\mu_x, \sigma_x^2/n)$$

$$\bar{y} \sim N(\mu_y, \sigma_y^2/m)$$

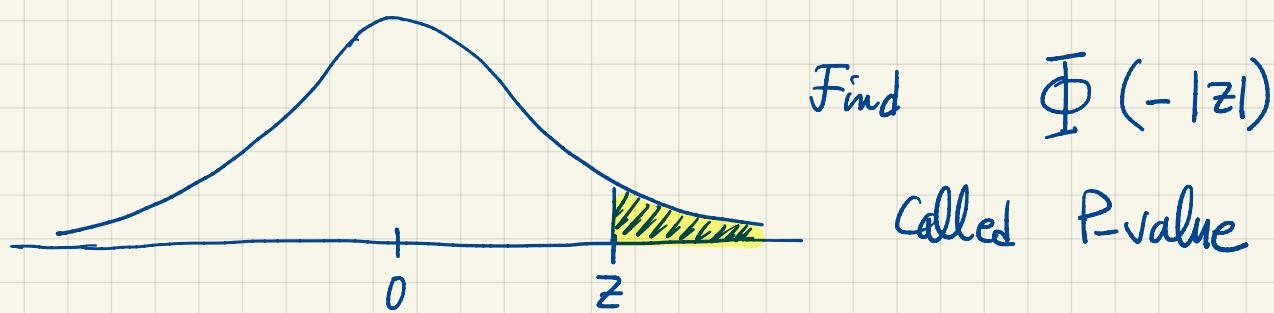
$$\bar{x} - \bar{y} \sim N(\mu_x - \mu_y, \frac{\sigma_x^2}{n} + \frac{\sigma_y^2}{m})$$

[linear combination]

$$z = \frac{\bar{x} - \bar{y} - (\mu_x - \mu_y)}{\sqrt{\frac{\sigma_x^2}{n} + \frac{\sigma_y^2}{m}}} \sim N(0, 1)$$

If  $\mu_x = \mu_y \Rightarrow \mu_x - \mu_y = 0$ , and

$$z = \frac{\bar{x} - \bar{y}}{\sqrt{\frac{\sigma_x^2}{n} + \frac{\sigma_y^2}{m}}} \sim N(0, 1)$$



If P-value is small, reject that  $\mu_x = \mu_y$

(because  $z$  is not likely to show up

either too small or too big)

Note: P-value is not  $P(\mu_x = \mu_y)$

## Bayesian approach

$$\mu_x | \bar{x} \sim N(m_1, v_1^2)$$

$$\mu_y | \bar{y} \sim N(m_2, v_2^2)$$

$$\mu_x - \mu_y | \bar{x}, \bar{y} \sim N(\underbrace{m_1 - m_2}_m, \underbrace{v_1^2 + v_2^2}_{v^2})$$

We have the density of  $\mu_x - \mu_y$  conditioned on  $\bar{x}$  and  $\bar{y}$ .

For instance, we can find  $P(\mu_x - \mu_y > b | \bar{x}, \bar{y}) = \Phi\left(\frac{m-b}{v}\right)$

This is now a little more informative since we can choose  $b$  as the threshold for what it means  $\mu_x \neq \mu_y$ .

Another way to look at this is to make  $\sigma^2 \rightarrow \infty$

in  $\mu \sim N(\beta, \sigma^2)$ . Then



$$\mu | \bar{x} \sim N(\bar{\mu}, \frac{\sigma_x^2}{n}) \quad [\text{same result as above}]$$

$$\mu_y | \bar{y} \sim N(\bar{\mu}_y, \frac{\sigma_y^2}{m})$$

$$\mu_x - \mu_y | \bar{x}, \bar{y} \sim N\left(\underbrace{\bar{\mu}_x - \bar{\mu}_y}_{m}, \underbrace{\frac{\sigma_x^2}{n} + \frac{\sigma_y^2}{m}}_{\sigma^2}\right)$$

$$P(\mu_x - \mu_y > b | \bar{x}, \bar{y}) = \Phi\left(\frac{m-b}{\sqrt{\frac{\sigma_x^2}{n} + \frac{\sigma_y^2}{m}}}\right)$$

$$\text{When } b=0, P(\mu_x > \mu_y | \bar{x}, \bar{y}) = \Phi\left(\frac{\bar{\mu}_x - \bar{\mu}_y}{\sqrt{\frac{\sigma_x^2}{n} + \frac{\sigma_y^2}{m}}}\right) = \Phi(z)$$

Recall, I defined P-value as  $\Phi(-|z|)$ .

$$P(\mu_x > \mu_y | \bar{x}, \bar{y}) = \begin{cases} 1 - P_{\text{value}} & z \geq 0 \\ \Phi(z) & z \leq 0 \end{cases}$$

Interpretation: P-value small and  $z \geq 0 \Rightarrow P(\mu_x > \mu_y | \bar{x}, \bar{y})$  high

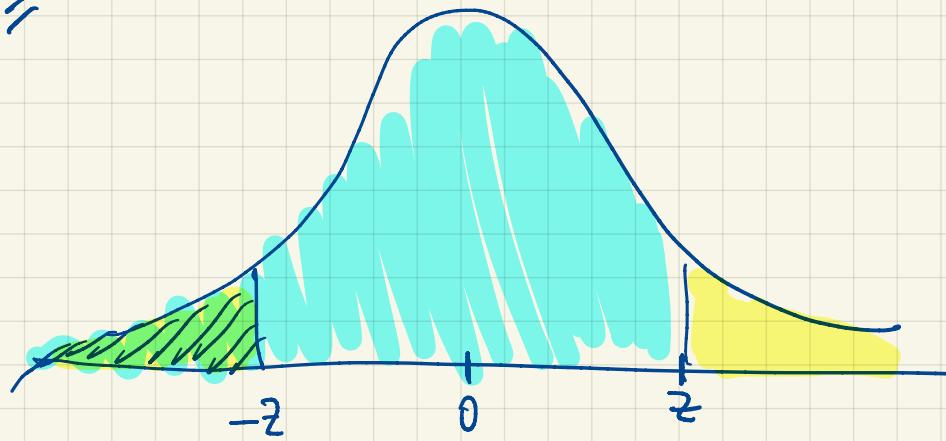
P-value small and  $z \leq 0 \Rightarrow P(\mu_y > \mu_x | \bar{x}, \bar{y})$  high

P-value moderate  $\Rightarrow P(\mu_x > \mu_y | \bar{x}, \bar{y})$   
 $P(\mu_y > \mu_x | \bar{x}, \bar{y})$  not high

Better interpretation of what P-value is.

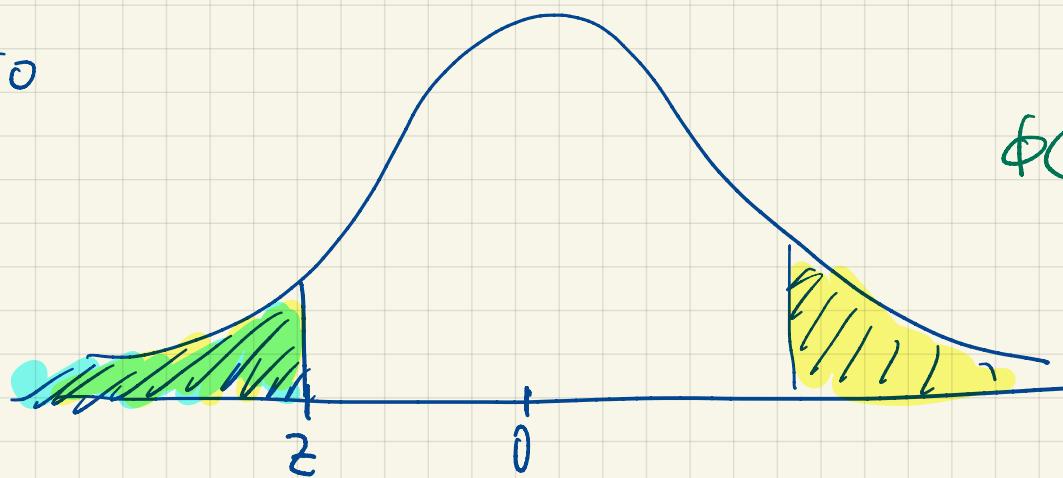
$$P\text{-value} = \Phi(-|z|)$$

$z > 0$



$$\phi(z) = 1 - P\text{-value}$$

$z \leq 0$



$$\phi(z) = P\text{-value}$$

## What does this all mean?

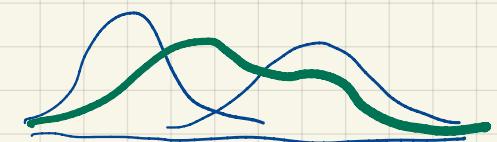
- Bayesian approach offers a more general framework and with a special choice for the prior, it boils down to the classical approach.
- This choice of prior is usually improper. We call it reference prior, because it brings us back to the non-Bayesian setting.
  - Reference prior was uniform from  $-\infty$  to  $+\infty$ , which meant I know nothing
- Another advantage of the Bayesian approach is that we can "mix" priors. ("not sure")

## Mixed Prior "Mixed feelings"

Assume prior is  $f(\theta) = \underbrace{\alpha g(\theta)}_{\text{Prior 1}} + \underbrace{\beta h(\theta)}_{\text{Prior 2}}$

Prior 1

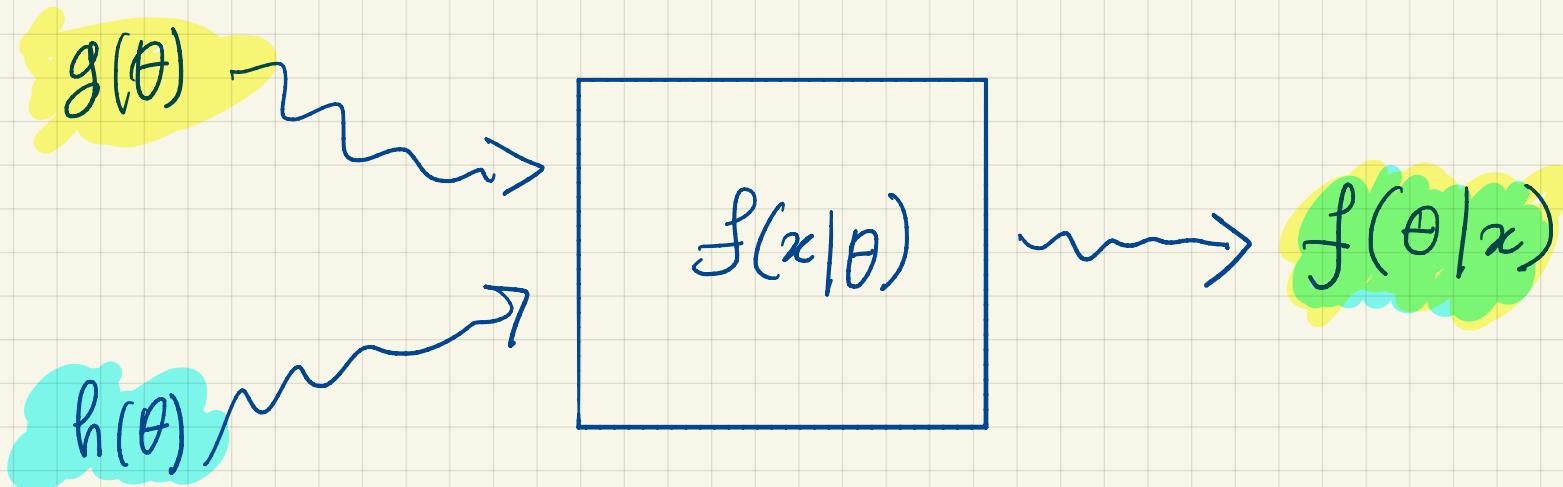
Prior 2



where  $\alpha + \beta = 1$ .

Observe:

$$\begin{aligned} \int f(\theta) d\theta &= \int [\alpha g(\theta) + \beta h(\theta)] d\theta \\ &= \alpha \int g(\theta) d\theta + \beta \int h(\theta) d\theta = \alpha + \beta = 1. \end{aligned}$$



$$f(\theta|x) = \frac{f(x|\theta) [\alpha g(\theta) + \beta h(\theta)]}{f(x)}$$

$$= \alpha \frac{f(x|\theta) g(\theta)}{f(x)} + \beta \frac{f(x|\theta) h(\theta)}{f(x)}$$

Now  $f(x|\theta)g(\theta) = g(\theta|x)g(x) = g(\theta|x) \int f(x|\theta)g(\theta)d\theta$

Similarly  $f(x|\theta)h(\theta) = h(\theta|x) \int f(x|\theta)h(\theta)d\theta$

$$f(\theta|x) = \frac{\alpha \int f(x|\theta)g(\theta)d\theta}{f(x)} g(\theta|x) + \frac{\beta \int f(x|\theta)h(\theta)d\theta}{f(x)} h(\theta|x)$$

$$= \alpha(x) g(\theta|x) + \beta(x) h(\theta|x)$$

where  $\alpha(x) + \beta(x) = 1$  and  $\frac{\alpha(x)}{\beta(x)} = \frac{\alpha}{\beta} \frac{\int f(x|\theta)g(\theta)d\theta}{\int f(x|\theta)h(\theta)d\theta}$

Example:  $x|\mu \sim N(\mu, 1)$

$$\mu \sim 0.5 N(0, 1) + 0.5 N(0, 2)$$

- if  $\mu \sim N(0, 1)$  then  $\mu|x \sim N\left(\frac{x}{2}, \frac{1}{2}\right)$
- if  $\mu \sim N(0, 2)$  then  $\mu|x \sim N\left(\frac{2x}{3}, \frac{2}{3}\right)$

Assume we are observing  $x=0$ , then

$\mu|x=0$  is a mixture of  $N(0, \frac{1}{2})$  and  $N(0, \frac{2}{3})$

What's the exact mixture?

$$\frac{\alpha(0)}{\beta(0)} = \frac{\int \frac{1}{\sqrt{2\pi}} e^{-\frac{\mu^2}{2}} \cdot \frac{1}{\sqrt{2\pi}} e^{-\frac{\mu^2}{2}} d\mu}{\int \frac{1}{\sqrt{2\pi}} e^{-\frac{\mu^2}{2}} \cdot \frac{1}{\sqrt{2\pi} \sqrt{2}} e^{-\frac{\mu^2}{4}} d\mu} \quad \alpha(0) + \beta(0) = 1$$

$$\frac{\alpha(0)}{\beta(0)} = \frac{\sqrt{2} \int \frac{1}{\sqrt{2\pi}} e^{-\frac{\mu^2}{2(\frac{1}{2})}} d\mu}{\int \frac{1}{\sqrt{2\pi}} e^{-\frac{\mu^2}{2(\frac{2}{3})}} d\mu}$$

$$= \frac{\sqrt{2} \sqrt{\frac{1}{2}}}{\sqrt{\frac{2}{3}}} = \sqrt{\frac{3}{2}}$$

and  $\int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{\mu^2}{2a}} d\mu = \sqrt{a}$

$$\int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi a}} e^{-\frac{\mu^2}{2a}} d\mu = 1$$

$$\alpha(0) = \underbrace{\sqrt{\frac{3}{2}}}_{\beta(0)} (1 - \alpha(0)) \Rightarrow \alpha(0) = \frac{\sqrt{\frac{3}{2}}}{1 + \sqrt{\frac{3}{2}}}$$

$$\beta(0) = \frac{1}{1 + \sqrt{\frac{3}{2}}}$$