

# Recap: Inference for Gaussian parameters

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# A sensor problem

- Noisy measurements from a sensor:  $x_1, x_2, \dots, x_n$
- Where is it located?

# A simple Gaussian Model

- Data modelled and generated i.i.d. from a Gaussian Distribution

$$\mathcal{N}(\mu, \sigma^2)$$

- Where  $\mu$  is the true but unknown position of the sensor and the variance  $\sigma^2$  is a noise parameter which is known.

# Likelihood

$$P(x_1, \dots, x_n \mid \mu, \sigma^2) = \prod_i^n \mathcal{N}(x_i \mid \mu, \sigma^2)$$

# Prior

$$P(\mu) = \mathcal{N}(\mu \mid \mu_0, \sigma_0^2)$$

$\mu_0$  and  $\sigma_0^2$  are **hyperparameters** that are known from prior domain knowledge

# Posterior

- Bayes Rule:

$$P(\mu \mid x_1, \dots, x_n) = \frac{\overset{\text{likelihood}}{\mathcal{N}(x_1, \dots, x_n \mid \mu, \sigma^2)} \overset{\text{prior}}{\mathcal{N}(\mu \mid \mu_0, \sigma_0^2)}}{\int_{-\infty}^{+\infty} \mathcal{N}(x_1, \dots, x_n \mid \mu, \sigma^2) \mathcal{N}(\mu \mid \mu_0, \sigma_0^2) d\mu}$$

Normalizing  
factor: **Bad Shit!**

# Conjugate Prior!

- Since we have used a conjugate prior to the likelihood, we know immediately that the resulting posterior distribution is also a Gaussian distribution without having to compute the denominator.

$$\mathcal{N}(\mu \mid \mu_n, \sigma_n)$$

- What are the parameters  $\mu_n, \sigma_n$  ?
- Pattern match with numerator of Bayes formula!

# Pattern Match!

$$P(\mu | x_1, \dots, x_n) = \frac{\mathcal{N}(x_1, \dots, x_n | \mu, \sigma^2) \mathcal{N}(\mu | \mu_0, \sigma_0^2)}{\int_{-\infty}^{+\infty} \mathcal{N}(x_1, \dots, x_n | \mu, \sigma^2) \mathcal{N}(\mu | \mu_0, \sigma_0^2) d\mu}$$

$$\mathcal{N}(\mu | \mu_n, \sigma_n)$$



Match exponents

$$\exp\left(-\frac{1}{2\sigma_n^2}(\mu - \mu_n)^2\right)$$

$$\exp\left(-\frac{1}{2\sigma^2}\sum_{i=1}^n(x_i - \mu)^2 - \frac{1}{2\sigma_0^2}(\mu - \mu_0)^2\right)$$

# Pattern Match

- Compare coefficient of  $\mu^2$ :

$$\frac{1}{\sigma_n^2} = \frac{1}{\sigma_0^2} + \frac{n}{\sigma^2}$$

- Compare coefficient of  $\mu$  and use above:

$$\mu_n = \frac{\sigma^2}{n\sigma_0^2 + \sigma^2} \mu_0 + \frac{n\sigma_0^2}{n\sigma_0^2 + \sigma^2} \mu_{ML}$$

$$\mu_{ML} = \frac{\sum_i x_i}{n}$$

# Model Selection: Which model is better?

- Suppose we have two models with variances

$$\sigma_1^2 \quad \text{and} \quad \sigma_2^2$$

- Which should one prefer?
- Compute Bayes Factor:

$$\frac{P_{M_1}(x_1, \dots, x_n)}{P_{M_2}(x_1, \dots, x_n)} = \frac{\mathcal{N}(x_1, \dots, x_n \mid \mu_{n,1}, \sigma_{n,1}^2)}{\mathcal{N}(x_1, \dots, x_n \mid \mu_{n,2}, \sigma_{n,2}^2)}$$