

## Question: Bias of the MAP Estimate for a Gaussian Mean

Let  $X_1, X_2, \dots, X_n$  be independent and identically distributed (i.i.d.) samples from a normal distribution:

$$X_i \sim \mathcal{N}(\mu, \sigma^2), \quad i = 1, 2, \dots, n$$

where  $\mu$  is the unknown mean and  $\sigma^2$  is known. Assume we place a normal prior on  $\mu$ :

$$\mu \sim \mathcal{N}(\mu_0, \tau^2).$$

1. Derive the Maximum A Posteriori (MAP) estimate of  $\mu$ .
2. Compute the expectation  $E[\hat{\mu}_{MAP}]$  and determine whether the MAP estimate is an unbiased estimator of  $\mu$ .

## Question: MAP Estimate for a Gaussian Mean with Uniform Prior

Let  $X_1, X_2, \dots, X_n$  be independent and identically distributed (i.i.d.) samples from a normal distribution:

$$X_i \sim \mathcal{N}(\mu, \sigma^2), \quad i = 1, 2, \dots, n$$

where  $\sigma^2$  is known, and  $\mu$  is the unknown mean.

We assume a \*\*uniform prior\*\* on  $\mu$ :

$$\mu \sim U(-1, 1)$$

1. Write down the likelihood function  $P(X|\mu)$  for the given data.
2. Derive the Maximum A Posteriori (MAP) estimate of  $\mu$ .
3. If the prior were  $U(-a, a)$ , how would the MAP estimate change?

## Question: Bias of Mean Estimator Based on Min and Max

Let  $D = \{X_1, X_2, \dots, X_n\}$  be independent and identically distributed (i.i.d.) samples from a normal distribution:

$$X_i \sim \mathcal{N}(\mu, \sigma^2), \quad i = 1, 2, \dots, n$$

We estimate the mean using:

$$\hat{\mu} = \frac{\min(D) + \max(D)}{2}$$

Find if  $\hat{\mu}$  is biased or unbiased estimator for the true mean  $\mu$ .

## Question: MAP Estimate for the Mean of a Multivariate Gaussian with a Multivariate Bernoulli Prior

Let  $X_1, X_2, \dots, X_n$  be independent and identically distributed (i.i.d.) samples from a multivariate normal distribution:

$$X_i \sim \mathcal{N}(\mu, \Sigma), \quad i = 1, 2, \dots, n$$

where:

- $\mu$  is the unknown mean vector of dimension  $d$ .
- $\Sigma$  is the known covariance matrix of size  $d \times d$ .

We assume a multivariate Bernoulli prior on  $\mu$ , where each component  $\mu_j$  follows an independent Bernoulli distribution:

$$P(\mu) = \prod_{j=1}^d p_j^{\mu_j} (1 - p_j)^{1 - \mu_j}, \quad \mu_j \in \{0, 1\}.$$

Compute the unnormalized (without evidence) posterior distribution  $P(\mu|X)$  and derive the MAP estimate  $\hat{\mu}_{MAP}$ .