

1.2 Probability Theory

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0.0.1 Derivation complement of equation 1.54

$$\begin{aligned} \ln p(\mathbf{x}|\mu, \sigma^2) &= \ln \prod_{n=1}^N \frac{1}{(2\pi\sigma^2)^{\frac{1}{2}}} \exp\left\{-\frac{1}{2\sigma^2}(X_n - \mu)^2\right\} \\ &= \ln[(2\pi\sigma^2)^{-\frac{N}{2}} \exp\left\{-\frac{1}{2\sigma^2} \sum_{n=1}^N (X_n - \mu)^2\right\}] \\ &= -\frac{N}{2} \ln(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{n=1}^N (x_n - \mu)^2 \\ &= -\frac{1}{2\sigma^2} \sum_{n=1}^N (x_n - \mu)^2 - \frac{N}{2} \ln\sigma^2 \ln(2\pi) \end{aligned}$$

0.0.2 Derivation complement of equation 1.55

$$\frac{\partial \ln p(\mathbf{x}|\mu, \sigma^2)}{\partial \mu} = \frac{1}{\sigma^2} \sum_{n=1}^N (x_n - \mu) = 0 \rightarrow \mu_{ML} = \frac{1}{N} \sum_{n=1}^N x_n$$

0.0.3 Derivation complement of equation 1.56

$$\frac{\partial \ln p(\mathbf{x}|\mu, \sigma^2)}{\partial \sigma^2} = -\frac{1}{2} \sum_{n=1}^N (X_n - \mu)^2 \cdot \left(-2 \cdot \frac{1}{\sigma^3}\right) - \frac{N}{2} \cdot \frac{2\sigma}{\sigma^2} = 0 \rightarrow \sigma_{ML}^2 = \frac{1}{N} \sum_{n=1}^N (x_n - \mu_{ML})^2$$

0.0.4 Derivation complement of equation 1.63

$$\frac{\partial p(\mathbf{t}|\mathbf{x}, w, \beta)}{\partial \beta} = -\frac{1}{2} \sum_{n=1}^N \{y(x_n m, \mathbf{w} - t_n)^2 + \frac{N}{2\beta}\} = 0 \rightarrow \frac{1}{\beta_{ML}} = \frac{1}{N} \sum_{n=1}^N \{y(x_n, \mathbf{w}_{ML}) - t_n\}^2$$

0.0.5 Comprehension about equation 1.68

I can understand the equation 1.68 intuitively, but I wanna make clear how to give a rigorous derivation. In a fully Bayesian approach, the data set x is observed(i.e. It is already known), so the unknown variables are w and the target value t . Thus we can simplify (1.68) by eliminating variable x

$$p(t) = \int p(t|\mathbf{w})p(\mathbf{w})d\mathbf{w} = \int p(t, \mathbf{w})d\mathbf{w}$$

This is easy to understand, we can model the joint distribution $\int p(t, \mathbf{w})d\mathbf{w}$ and then marginalize it to obtain the probability $p(t)$

Substituting the data variable x , these equation will look like this:

$$p(t) = \int p(t|\mathbf{w})p(\mathbf{w})d\mathbf{w} = \int p(t, \mathbf{w})d\mathbf{w}$$

Reference

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URL <https://www.zhihu.com/question/44532390/answer/99662629>

SourceZhihu

0.0.6 Derivation complement from 1.69 to 1.72

I totally didn't understand the equation 1.69-1.72 at the first, such many mathematical symbols showing up in the meantime scare the shit out of me, but I believe I can figure it out for the next time!