

# Lecture 15: Advanced topics in Bayesian linear regression

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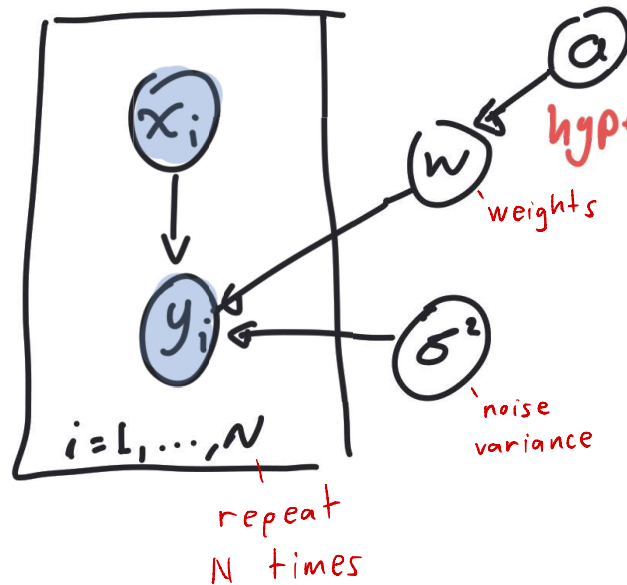
## The evidence approximation

# Open questions

- How do I quantify the measurement noise?
  - How do we avoid overfitting?
  - How do I quantify epistemic uncertainty induced by limited data?
  - How do I choose any remaining parameters?  
↳ evidence approximation
  - How do I choose which basis functions to keep?
- } remaining problems to address

# Hyper-priors

blue =  
observed



Prior:

$$\begin{cases} \alpha \sim p(\alpha) \\ \underline{w} | \alpha \sim p(\underline{w} | \alpha) = \mathcal{N}(\underline{w} | 0, \alpha^{-1} \mathbb{I}) \\ \sigma \sim p(\sigma) \end{cases}$$

Likelihood:

$$y_i | x_i, \underline{w}, \sigma^2 \sim \mathcal{N}(\phi^T(x_i) \underline{w}, \sigma^2)$$

$$\hookrightarrow p(y_{1:N} | x_{1:N}, \underline{w}, \sigma^2) = \prod_{i=1}^N \dots$$

# Posterior over hyper-parameters and the evidence approximation

$$p(\underline{w}, \alpha, \sigma | x_{1:n}, y_{1:n}) \propto \underbrace{p(y_{1:n} | x_{1:n}, \underline{w}, \sigma)}_{\text{likelihood}} \underbrace{p(\underline{w} | \alpha)}_{\text{prior}} \underbrace{p(\alpha)}_{\text{hyper-prior}} \underbrace{p(\sigma)}_{\text{prior}}$$

$$\begin{aligned} p(\alpha, \sigma | x_{1:n}, y_{1:n}) &= \int p(\underline{w}, \alpha, \sigma | x_{1:n}, y_{1:n}) d\underline{w} \\ &\propto \int p(y_{1:n} | x_{1:n}, \underline{w}, \sigma) p(\underline{w} | \alpha) \boxed{p(\alpha) p(\sigma)} d\underline{w} \\ &= \int \underbrace{p(y_{1:n} | x_{1:n}, \underline{w}, \sigma)}_{\text{prop. to } p(\underline{w} | x_{1:n}, y_{1:n}, \alpha, \sigma)} p(\underline{w} | \alpha) d\underline{w} p(\alpha) p(\sigma) \end{aligned}$$

$\therefore$  this integral is the normalization constant

the normalization constant of the posterior of the weights conditioned on  $\alpha$  &  $\sigma$

$$= Z(\alpha, \sigma) p(\alpha) p(\sigma)$$

$N(\underline{w} | \underline{w}(\alpha, \sigma), \Sigma(\alpha, \sigma))$

$p(\underline{w} | x_{1:n}, y_{1:n}, \alpha, \sigma) \propto p(y_{1:n} | x_{1:n}, \underline{w}, \sigma) \cdot p(\underline{w} | \alpha)$



PREDICTIVE  
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Evidence approximation<sup>4</sup>: Find  $\alpha, \sigma$  by maximizing their posterior (with  $\underline{w}$  integrated out).

$$\alpha^*, \sigma^* = \arg \max_{\alpha, \sigma} p(\alpha, \sigma | x_{1:n}, y_{1:n})$$

# Example

