

# Lecture 15: Advanced topics in Bayesian linear regression

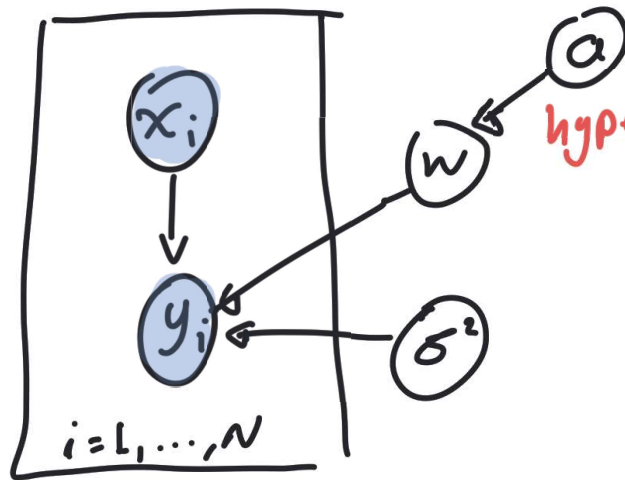
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## The evidence approximation

# 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?
- How do I choose which basis functions to keep?

# Hyper-priors



hyper-parameter

Prior:  $\alpha \sim p(\alpha)$

$$\underline{w} | \alpha \sim p(\underline{w} | \alpha) = \mathcal{N}(\underline{w} | 0, \alpha^{-1} \mathbf{I})$$

$$\sigma \sim p(\sigma)$$

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

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

$$p(\alpha, \sigma | x_{1:n}, y_{1:n}) = \int \underbrace{p(\underline{w}, \alpha, \sigma | x_{1:n}, y_{1:n})}_{\substack{\propto p(y_{1:n} | x_{1:n}, \underline{w}, \sigma) p(\underline{w} | \alpha) p(\alpha) p(\sigma)}} d\underline{w}$$

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

$$= \int \underbrace{p(y_{1:n} | x_{1:n}, \underline{w}, \sigma) p(\underline{w} | \alpha)}_{\substack{p(\underline{w} | x_{1:n}, y_{1:n}, \alpha, \sigma) \propto p(y_{1:n} | x_{1:n}, \underline{w}, \sigma) \cdot p(\underline{w} | \alpha)}} d\underline{w} p(\alpha) p(\sigma)$$

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

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

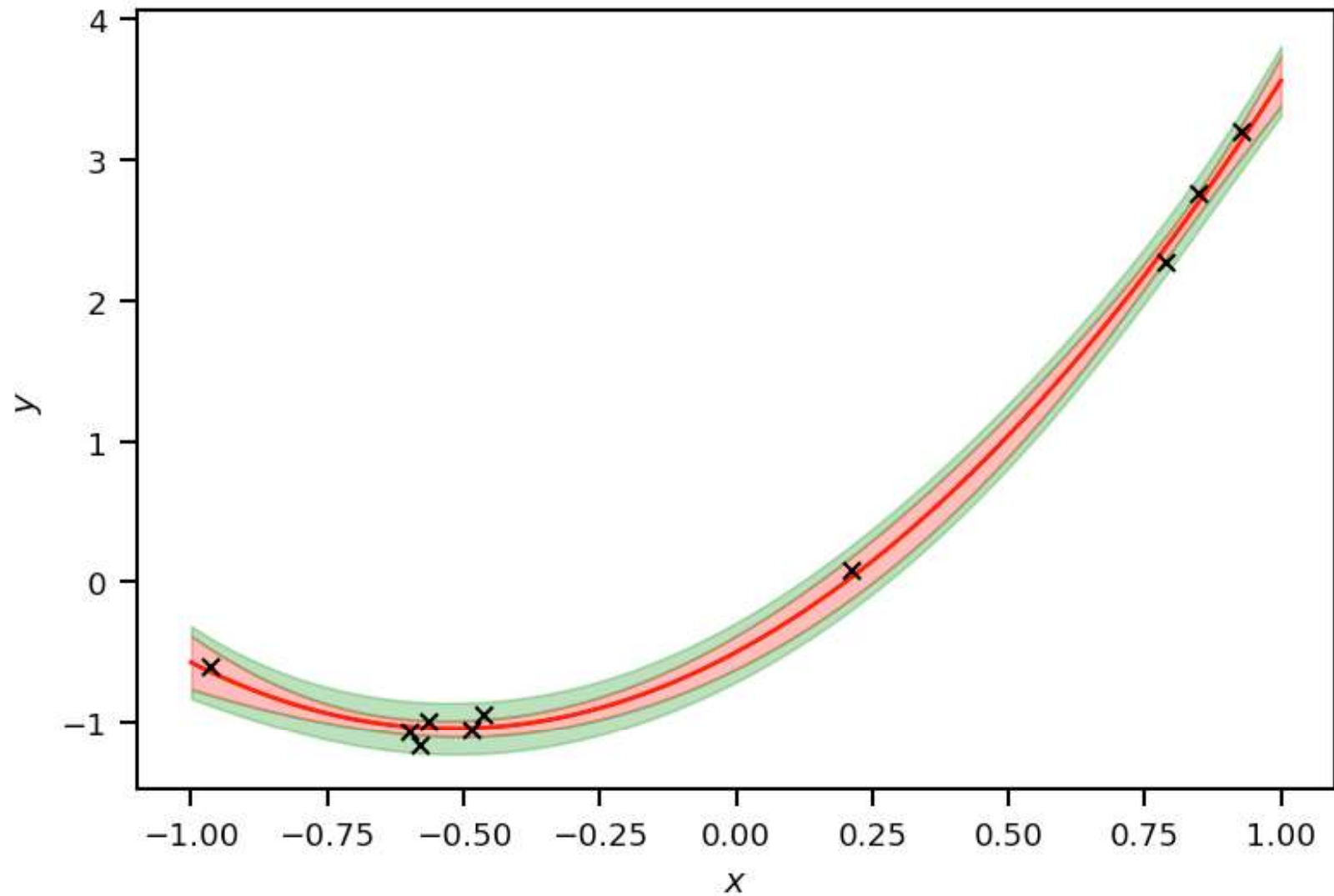


PREDICTIVE  
SCIENCE LABORATORY

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



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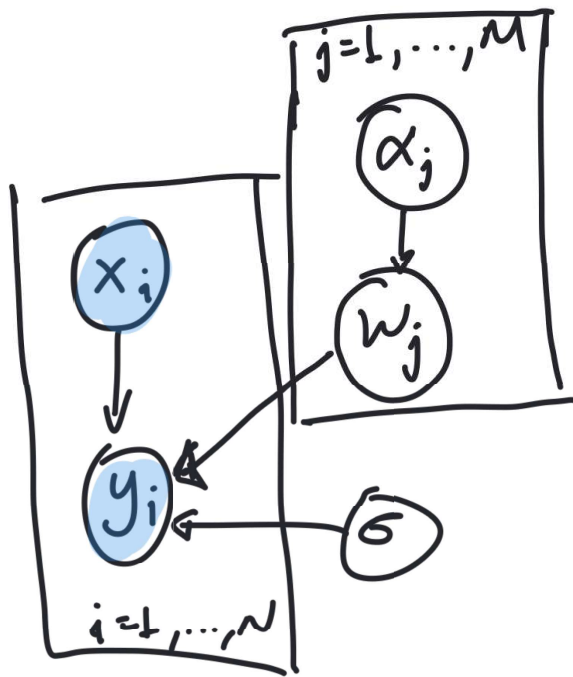
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## Automatic relevance determination

# Open questions

- How do I quantify the measurement noise?
- How do we avoid overfitting?
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# Idea: Different hyper-prior per weight



Prior:

$$\alpha_j \sim p(\alpha_j)$$

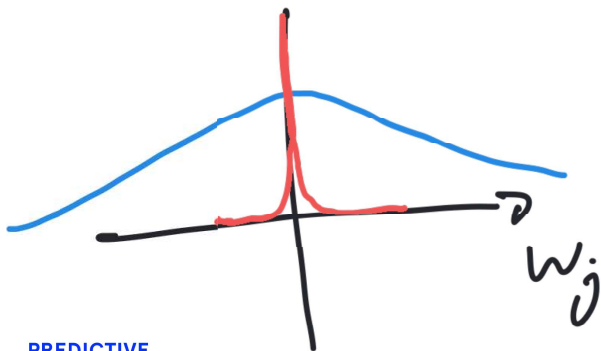
$$w_j | \alpha_j \sim p(w_j | \alpha_j) = \underline{N(w_j | 0, \sigma_j^{-1})}$$

$$\sigma \sim p(\sigma)$$

Likelihood:

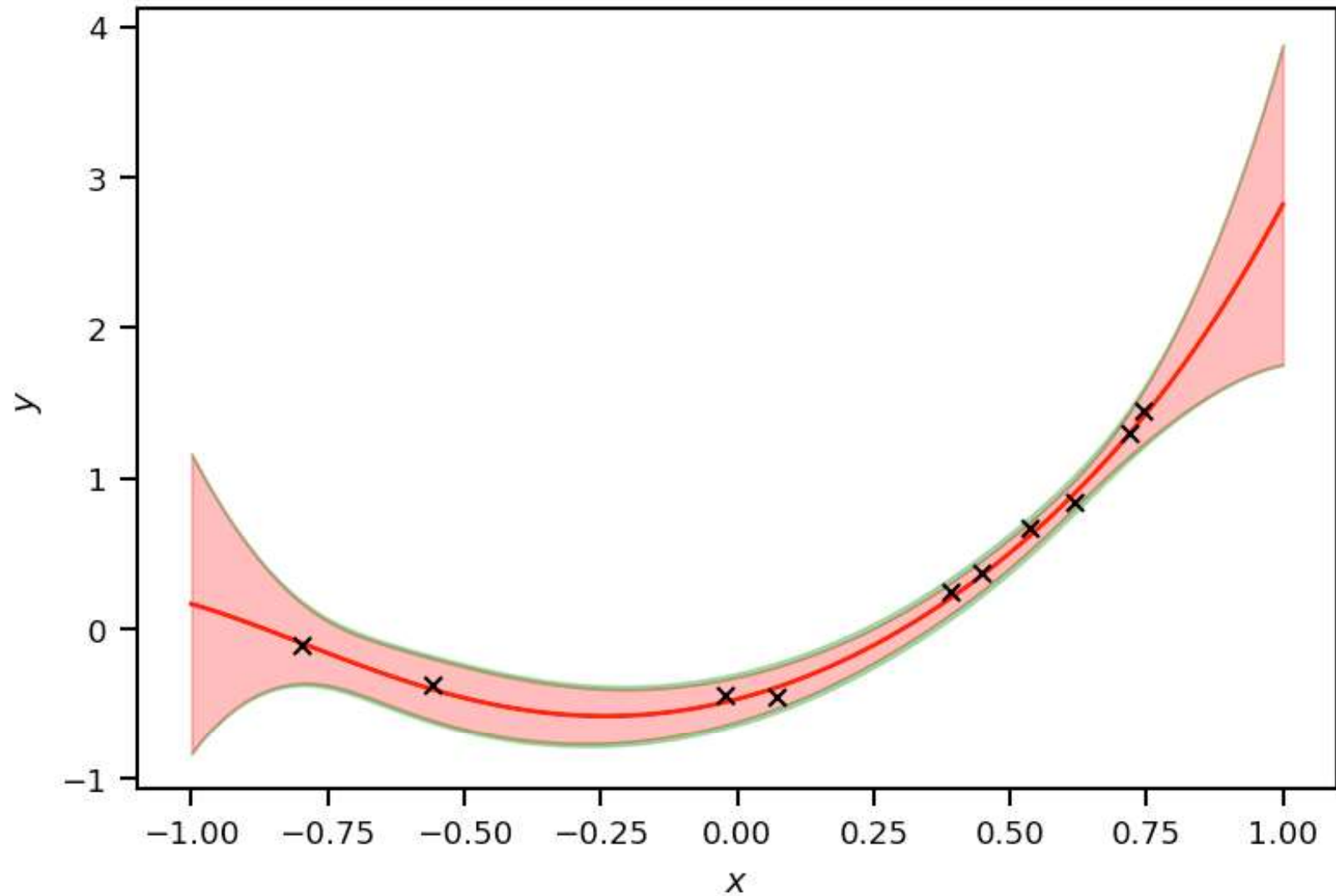
$$\underline{a}^*, \sigma^* = \arg \max_{\underline{a}, \sigma} p(\underline{a}, \sigma | x_{1:n}, y_{1:n})$$

$$\alpha_j \gg 1$$

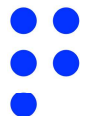
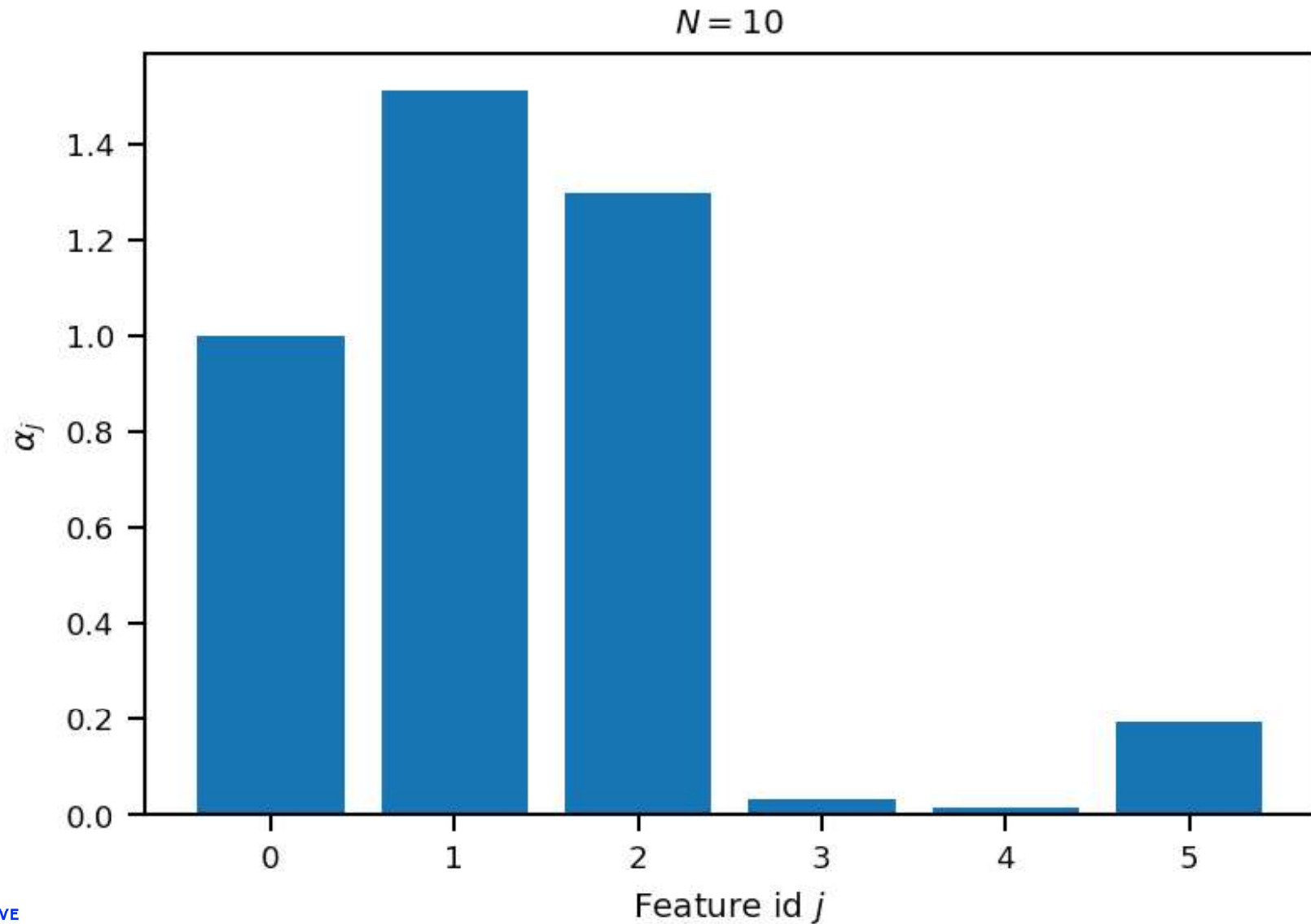




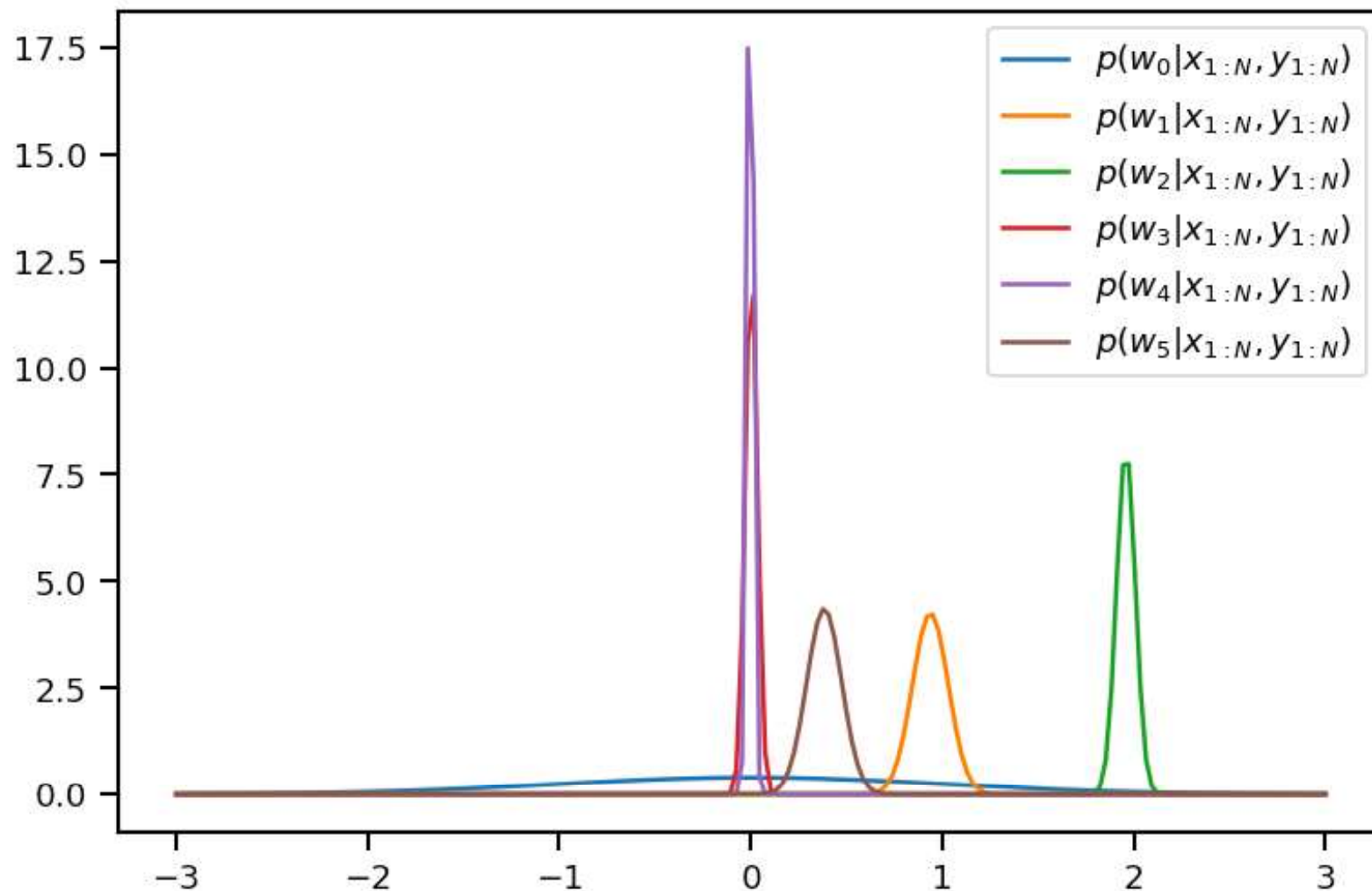
# Example



# Optimized values for the $\alpha_j$ 's



# Marginal posteriors for the weights



# Open questions

- Cannot be used to compare generalized models with other models (e.g., of completely different functional form). For this, we will need Bayesian model selection.
- How can we model the fact that our noise is input-dependent (heteroscedastic)?

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## Diagnostics for posterior predictive

# Standardized errors

Post. pred.  $p(y|x, \text{data}) = N(y | \mu(x), \sigma^2(x))$

Validation data:  $x_i, y_i, i=1, \dots, N^v$

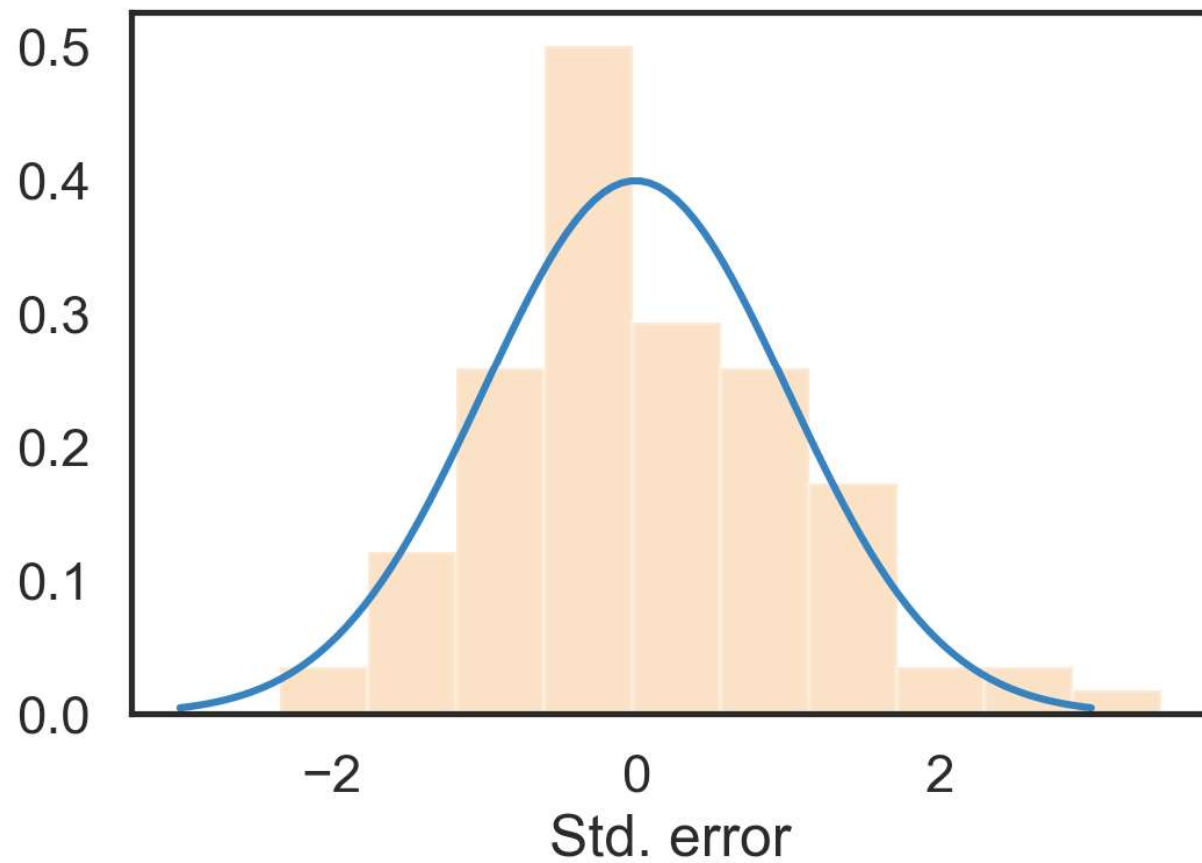
model says:  $y_i | x_i \sim N(\mu(x_i), \sigma^2(x_i))$  ←

Standardized Error:  $z_i := \frac{y_i - \mu(x_i)}{\sigma(x_i)} \sim N(0, 1)$  (If model is correct)

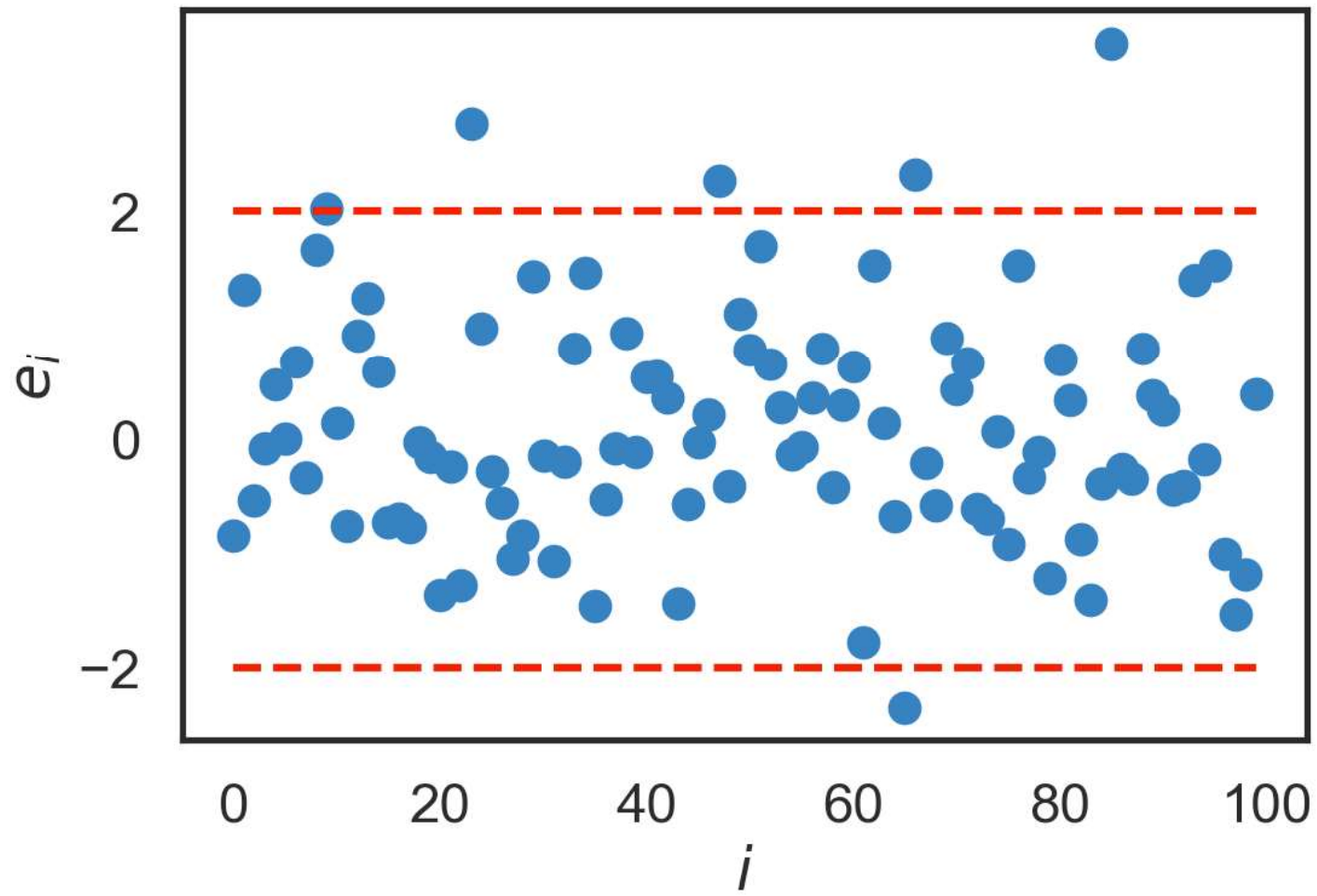
$$E[z_i] = E\left[\frac{y_i - \mu(x_i)}{\sigma(x_i)}\right] = \frac{E[y_i] - \mu(x_i)}{\sigma(x_i)} = 0$$

$$V[z_i] = V\left[\frac{y_i - \mu(x_i)}{\sigma(x_i)}\right] = \frac{1}{\sigma^2(x_i)} V[y_i] = \frac{\sigma^2(x_i)}{\sigma^2(x_i)} = 1$$

# Standardized Errors



# Standardized Errors





# Standardized Errors

