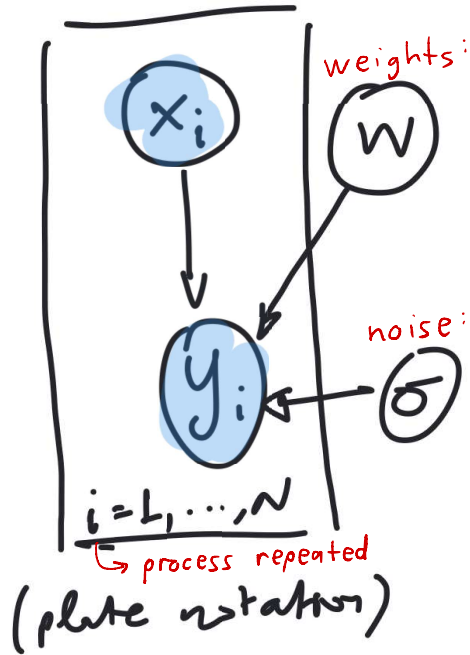


Open questions

- 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?

Probabilistic interpretation



Prior: $\underline{w} \sim p(\underline{w})$
 $\sigma \sim p(\sigma)$

Likelihood:

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

conditionally independent

$$P(y_{1:N} | x_{1:N}, \underline{w}, \sigma^2) \stackrel{\sim}{=} \prod_{i=1}^N p(y_i | x_i, \underline{w}, \sigma^2)$$

$$= \prod_{i=1}^N (2\pi)^{-1/2} \sigma^{-1} \exp \left\{ -\frac{(y_i - \phi^T(x_i) \underline{w})^2}{2\sigma^2} \right\}$$

square error

$$= (2\pi)^{-N/2} \sigma^{-N} \exp \left\{ -\frac{1}{2\sigma^2} \sum_{i=1}^N (y_i - \phi^T(x_i) \underline{w})^2 \right\}$$

Posterior \propto Likelihood \cdot Prior

$$P(\underline{w}, \sigma | x_{1:N}, y_{1:N}) \propto \underbrace{P(y_{1:N} | x_{1:N}, \underline{w}, \sigma^2)}_{\text{assume}} p(\underline{w}) p(\sigma)$$

assume

Maximum likelihood estimate of weights yields least squares

$$\log p(y_{1:N} | x_{1:N}, \underline{w}, \sigma) = -\frac{N}{2} \log 2\pi - N \log \sigma - \frac{1}{2\sigma^2} \sum_{i=1}^N (y_i - \underbrace{\underline{\phi}^T(x_i) \underline{w}}_{L(\underline{w})})^2$$

$$\max_{\underline{w}} \log \text{like} \equiv \min_{\underline{w}} L(\underline{w})$$

$$\therefore \underline{\Phi}^T \underline{\Phi} \underline{w} = \underline{\Phi}^T \underline{y}$$

For σ :

$$\frac{\partial}{\partial \sigma} (\log \text{like}) = 0 \rightarrow \sigma = \frac{1}{N} \sum_{i=1}^N (y_i - \underline{\phi}^T(x) \underline{w})^2$$

