Point-predictive distribution

$p(y \mid \underline{x}, x_{1:N}, y_{1:N}, a, \sigma^2) = ?$

measurement likelihood

posterior $\underline{p(\underline{w} \mid x_{1:N}, y_{1:N}, a, \sigma^2)} = \checkmark$; $\underline{p(y \mid x, \underline{w}, \sigma^2)} = \checkmark$

Sum Rule: $p(A \mid I) = \sum_i p(A \mid B_i, I)\, p(B_i \mid I)$

$p(B_1 \text{ or } B_2 \text{ or } \dots) = 1$, $p(B_i, B_j) = 0$ B's form a partition

$$\underset{A}{p(y} \mid \underbrace{x, x_{1:N}, y_{1:N}, a, \sigma^2}_{I}) = \sum_i p(y \mid B_i, I)\, p(B_i \mid I)$$

$$= \int p(y \mid \underline{w}, I)\, p(\underline{w} \mid I)\, d\underline{w}$$

$p(\underline{w} \mid x_{1:N}, y_{1:N}, a, \sigma^2)$ posterior

likelihood

$p(y \mid \underline{w}, x, \cancel{x_{1:N}, y_{1:N}}, \cancel{a}, \sigma^2) = p(y \mid x, \underline{w}, \sigma^2)$

these have no influence on the condition

$$= \int p(y \mid x, \underline{w}, \sigma^2)\, p(\underline{w} \mid x_{1:N}, y_{1:N}, a, \sigma^2)\, d\underline{w}$$

$$= N(y \mid \underline{\varphi}^T(x)\, \underline{m},\ \underline{\varphi}^T(x)\, \underline{\underline{S}}\, \underline{\varphi}(x) + \sigma^2)$$

post. mean of weights

post. cov. of weights

epistemic

noise variance

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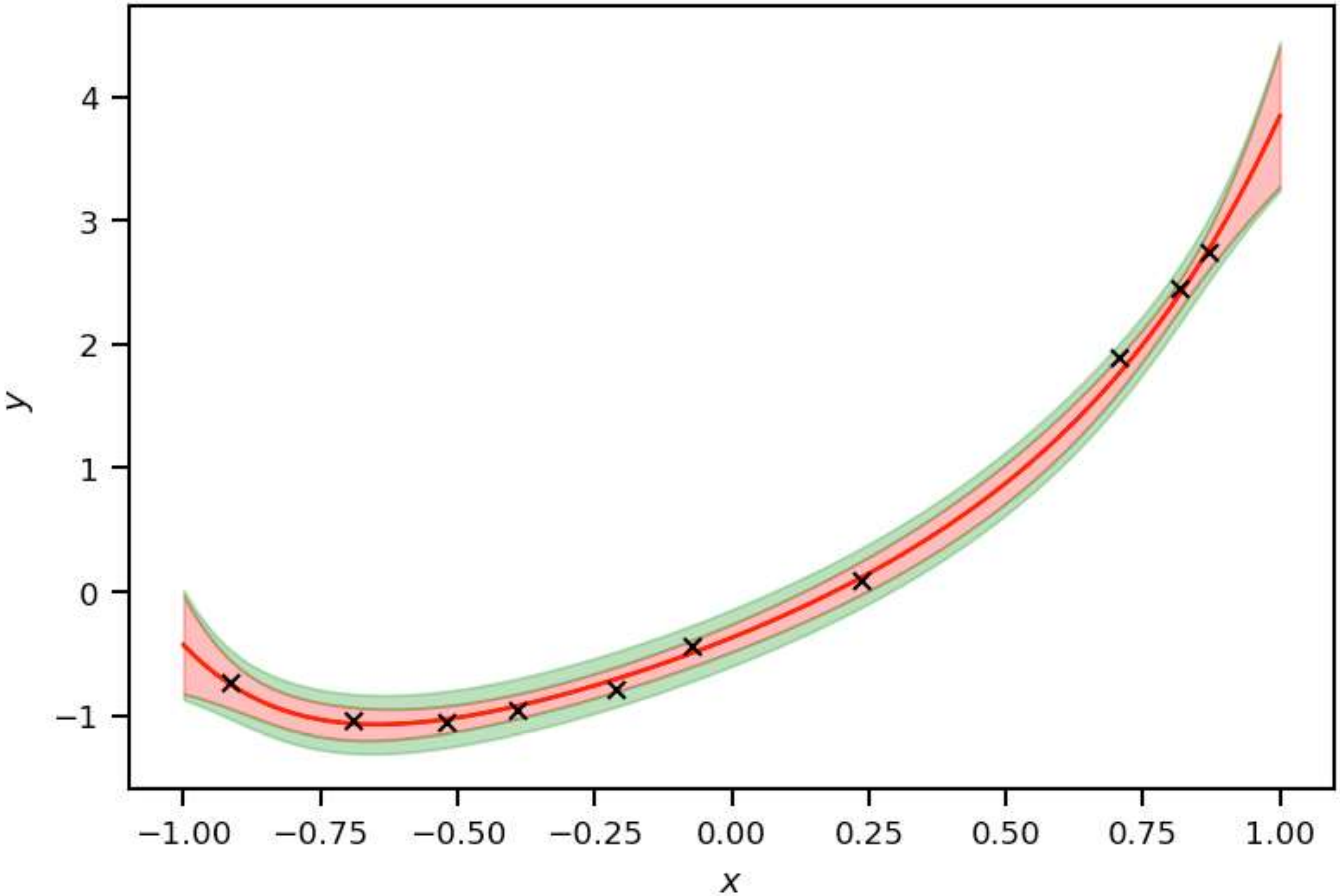
Example: Separating epistemic and aleatory uncertainties



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