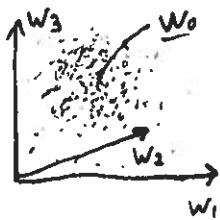


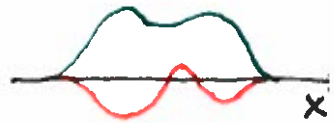
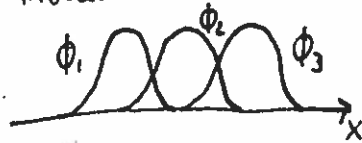
Bayesian update with basis functions

Prior: $p(\underline{w}) = \mathcal{N}(\underline{w}; \underline{w}_0, V_0)$ like before



Prior also includes model choices ∇

Samples from prior



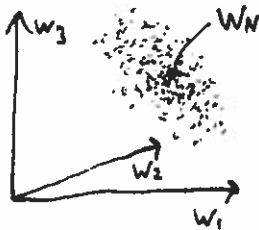
Bayes' Rule + data

→ Posterior $p(\underline{w} | D) = \mathcal{N}(\underline{w}; \underline{w}_N, V_N)$

don't memorize:

$$V_N = \sigma_y^2 (\sigma_y^2 V_0^{-1} + \Phi^T \Phi)^{-1}$$

$$\underline{w}_N = V_N V_0^{-1} \underline{w}_0 + \frac{1}{\sigma_y^2} V_N \Phi^T \underline{y}$$



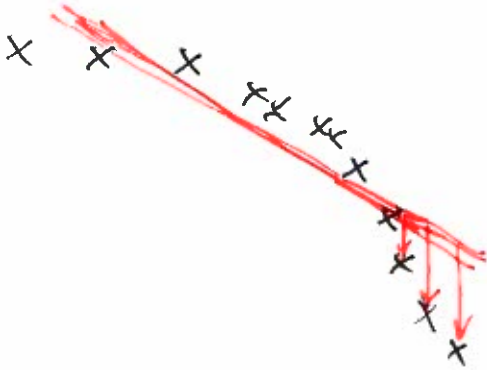
Samples from posterior $p(\underline{w} | D)$



Likelihood

$$p(y | x, \underline{w}) = \mathcal{N}(y; \Phi \underline{w}, \sigma_y^2)$$

"Underfitting"



No basis functions

Simple model
 \Rightarrow over-confident

Residuals

Correlations of Residuals

\rightarrow Model checking

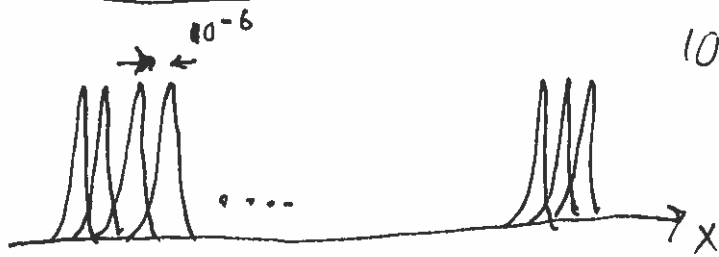
Overfitting

The Bayesian Method does not involve fitting.

\Rightarrow Don't overfit

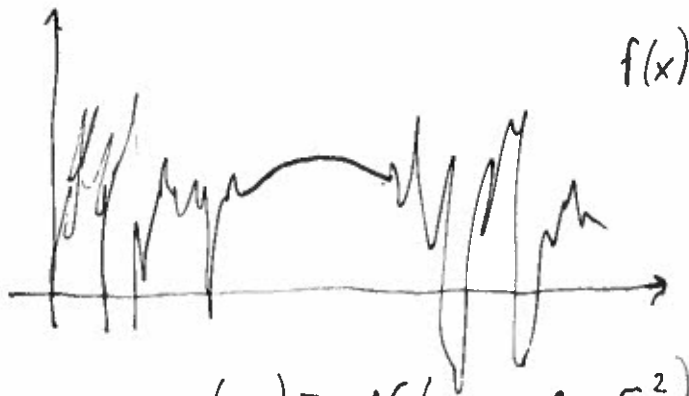
But...

Extremely flexible model



10^6 basis functions
(RBFs)

Can represent the function

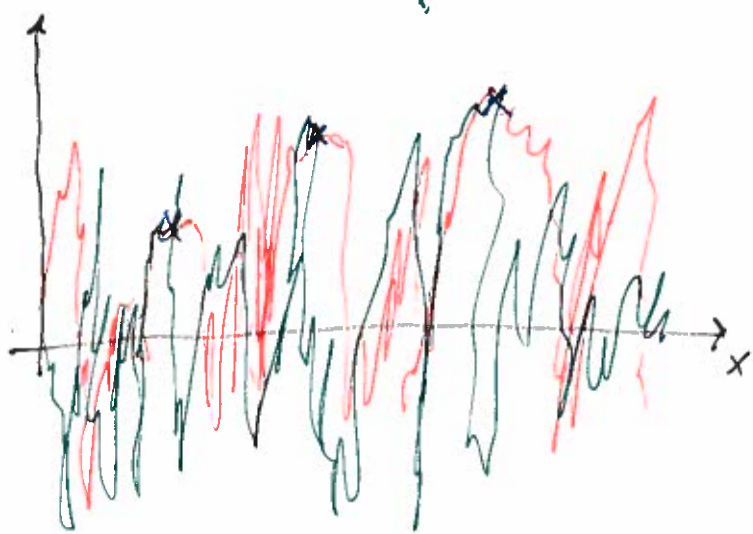
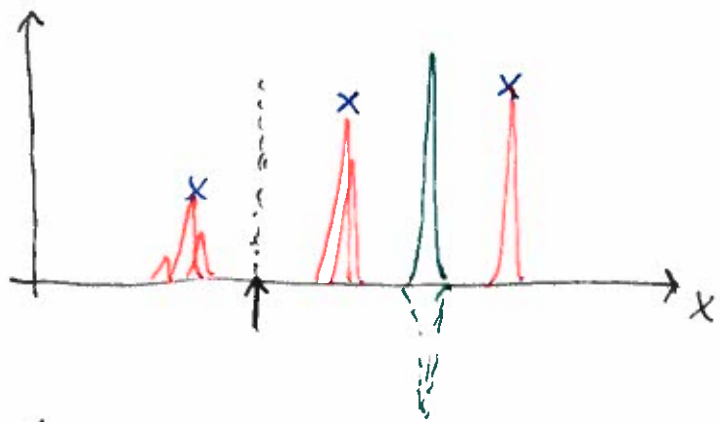


prior: $p(w_k) = \mathcal{N}(w_k; 0, \sigma_w^2)$
for each function k
 $k = 1, \dots, 10^6$

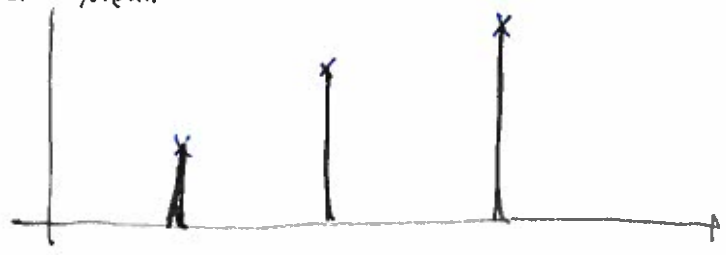
$$p(\underline{w}) = \mathcal{N}(\underline{w}; \underline{0}, \sigma_w^2 \mathbb{I})$$

big matrix

Posterior for the flexible model

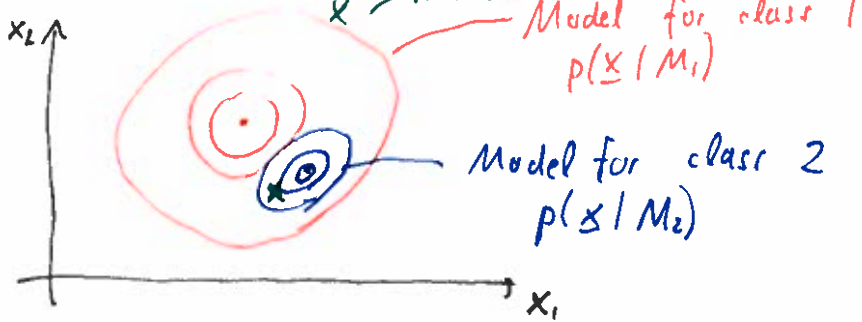


Posterior Mean



Probabilistic model choice

E.g. Bayes classifiers



Used likelihood of model
'fitted'

Model choice for regression

$p(y | X, M)$ — Model choices
 $\sigma_y^2, V_0 = \sigma_w^2 I, w_0 = 0, \Phi, \dots$
 └ Training inputs
 └ All training labels

"Marginal likelihood"

or just "likelihood" of the model

Could apply:

- ① Bayes' rule $\leadsto p(M | y, X)$
- ② Maximise likelihood

$$p(y | X, M) = \int p(y, \underline{w} | X, M) d\underline{w}$$

Sum rule

$$= \int \underbrace{p(y | X, \underline{w}, M)}_{\text{"Standard" likelihood}} \underbrace{p(\underline{w} | X, M)}_{\text{Prior}} d\underline{w}$$

Trick to solve integral:

Posterior weights:

$$\underbrace{p(\underline{w} | y, X, M)}_{p(\underline{w} | D)} = \frac{p(y | \underline{w}, X, M) \cdot p(\underline{w} | X, M)}{p(y | X, M)}$$

known

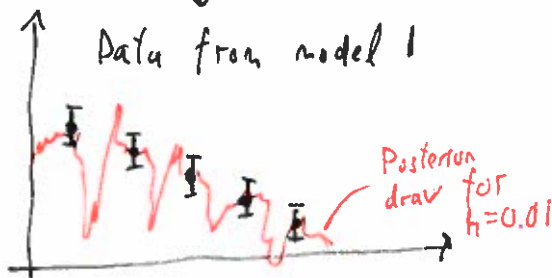
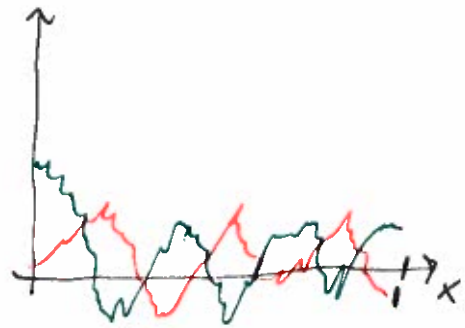
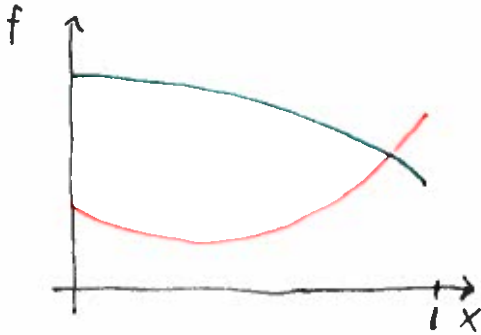
Rearrange and evaluate

Example model choice

100 basis functions, spaced between 0, 1

Model 1: Bandwidth $h=1$

Model 2: $h=0.01$



$$p(y|X, h=1) \gg p(y|X, h=0.01)$$

$$p(y|X, h=0.01, \hat{w}) \text{ big}$$