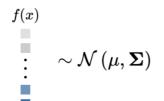
Advanced Machine Learning

Gaussian Processes: From Weight-space to Function-space



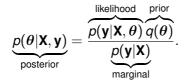


Learning goals

 The difference between weight-space and function-space views

WEIGHT-SPACE VIEW

- Until now we considered a hypothesis space \mathcal{H} of parameterized functions $f(\mathbf{x} \mid \theta)$ (in particular, the space of linear functions).
- Using Bayesian inference, we derived distributions for θ after having observed data \mathcal{D} .
- ullet Prior believes about the parameter are expressed via a prior distribution $q(\theta)$, which is updated according to Bayes' rule





WEIGHT-SPACE VS. FUNCTION-SPACE VIEW

Weight-Space View

Function-Space View

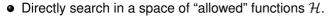
Parameterize functions

Example: $f(\mathbf{x} \mid \boldsymbol{\theta}) = \boldsymbol{\theta}^{\top} \mathbf{x}$

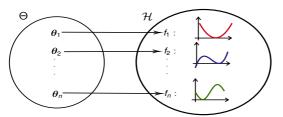
Define distributions on θ Define of

Define distributions on f

Inference in parameter space Θ — Inference in function space ${\mathcal H}$

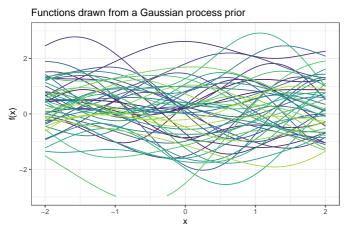


 Specify a prior distribution over functions instead over a parameter and update it according to the observed data points.





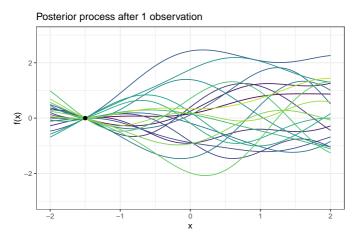
Intuitively, imagine we could draw a huge number of functions from some prior distribution over functions (*).



(*) We will see in a minute how distributions over functions can be specified.

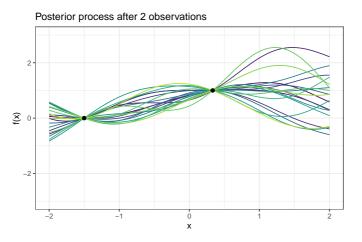


After observing some data points, we are only allowed to sample those functions, that are consistent with the data.



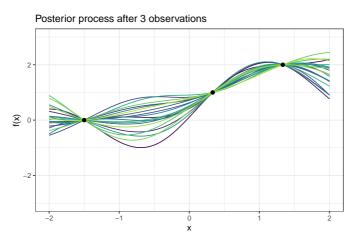


After observing some data points, we are only allowed to sample those functions, that are consistent with the data.



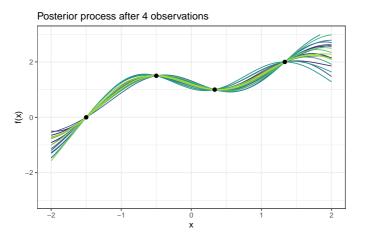


After observing some data points, we are only allowed to sample those functions, that are consistent with the data.





As we observe more and more data points, the variety of functions consistent with the data shrinks.





Intuitively, there is something like "mean" and a "variance" of a distribution over functions.

