Modern Gaussian Processes: Scalable Inference and Novel Applications

(Part IV) Theory & Code

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1 Theory for GPs

Asymptotics & Consistency

GPs & Stochastic Differential Equations

Other Interesting Topics



Theory for GPs

• The GP posterior mean minimizes the following functional:

$$J(f) = \frac{1}{2} \|f\|_{\mathcal{H}}^2 + \frac{1}{2\sigma^2} \sum_{i=1}^n (\mathbf{y}_i - f(\mathbf{x}_i))$$

where $||f||_{\mathcal{H}}^2$ is the RKHS norm corresponding to the covariance function κ .

• What happens when $N \to \infty$?

• The GP posterior mean minimizes the following functional:

$$J(f) = \frac{1}{2} \|f\|_{\mathcal{H}}^2 + \frac{1}{2\sigma^2} \sum_{i=1}^n \left(\mathbf{y}_i - f(\mathbf{x}_i) \right)$$

where $||f||_{\mathcal{H}}^2$ is the RKHS norm corresponding to the covariance function κ .

- What happens when $N \to \infty$?
- f converges to $\mathbb{E}_{p(y,\mathbf{x})}[y|\mathbf{x}] \dots$
- ... under some regularity conditions (nondegenerate κ, regression function well-behaved)

GPs & Stochastic Differential Equations

• Consider the Markov process:

$$a_m \frac{d^m f(x)}{dx^m} + a_{m-1} \frac{d^{m-1} f(x)}{dx^{m-1}} + \dots a_1 \frac{df(x)}{dx} + a_0 f(x) = w(x)$$

where w(x) is a zero-mean white-noise process.

- The solution is a GP
- The covariance depends on the form of the SDE
- Solving SDEs is easy in low dimensions!
- We can solve GPs in $\mathcal{O}(N \log N)$

- Average-case Learning Curves
- PAC-Bayesian Analysis
- Theory for Sparse GPs Best Paper Award ICML 2019

Code

- python
 - ► GPy
- MatLab
 - ► gptoolbox
- R
- kernlab

- TensorFlow:
 - ► GPflow
 - ► AutoGP
- PyTorch
 - ► CandleGP

- TensorFlow:
 - ► GPflow
 - Doubly-Stochastic DGPs
- PyTorch
 - DGPs with Random Features
- Theano
 - ► DGPs with Inducing Points & Exp. Propagation