

Probabilistic Numerics

Philipp Hennig, John Cunningham, Michael Osborne

Lake Tahoe
08 December 2012



Numerical Analysis is Inference ...

being uncertain about deterministic problems

numerical problems: use evaluations of f to estimate

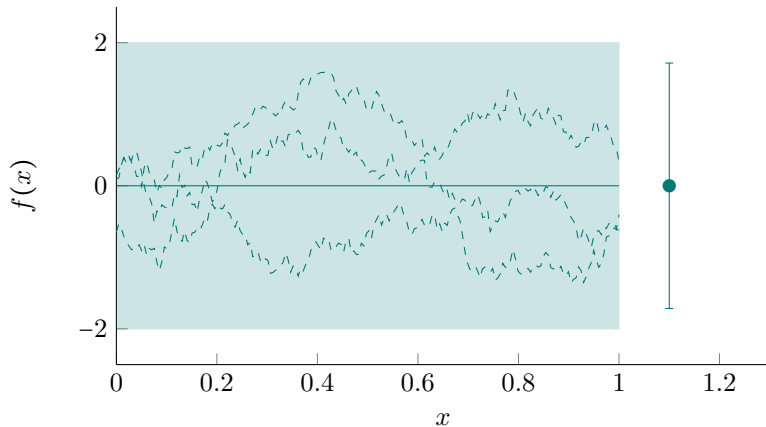
- $Z = \int f(x) dx$ quadrature
- samples from $p(x) = f(x)/Z$ Monte Carlo
- $\operatorname{argmin}_x f(x)$ optimization
- optimal trajectory under dynamics $f(x, t, u)$ planning / control

f is deterministic for the user of the algorithm, but uncertain for the designer of the algorithm.

- B. Ajne, T. Dalenius.
“Några tillämpningar av statistiska ideer på numerisk integration”
Nordisk Math. Tidskrift, 1960
- P. Diaconis. “Bayesian Numerical Analysis”
Statistical Decision Theory and Related Topics, 1988
- D. Calvetti & Erkki Somersalo. “Introduction to Bayesian Scientific Computing”
Springer, 2007

Example: ℓ_2 optimal quadrature

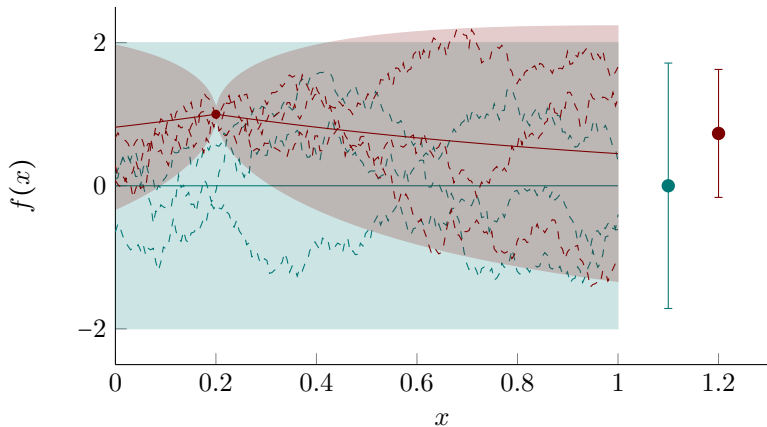
over a Gaussian process prior [c.f. Minka, 2000]



- say what functions you expect to need to integrate

Example: ℓ_2 optimal quadrature

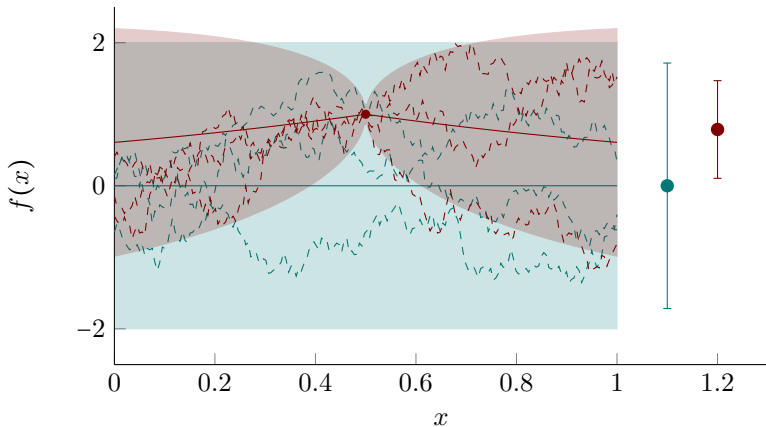
over a Gaussian process prior [c.f. Minka, 2000]



- ▶ say what functions you expect to need to integrate
- ▶ study how uncertainty drops from evaluation at x

Example: ℓ_2 optimal quadrature

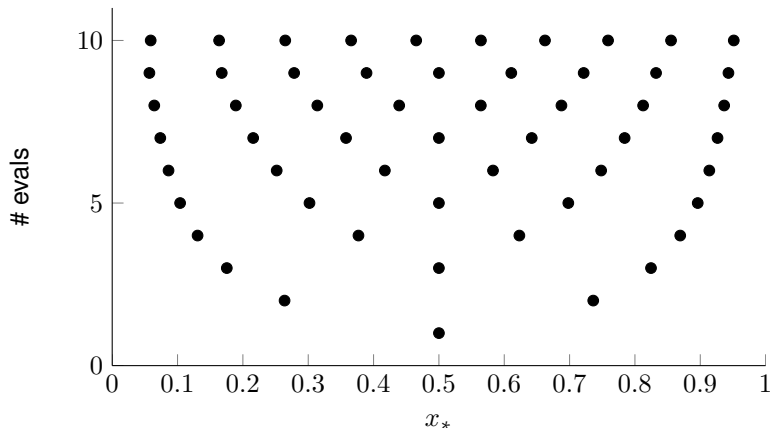
over a Gaussian process prior [c.f. Minka, 2000]



- ▶ say what functions you expect to need to integrate
- ▶ study how uncertainty drops from evaluation at x
- ▶ find x minimizing expected square error

Example: ℓ_2 optimal quadrature

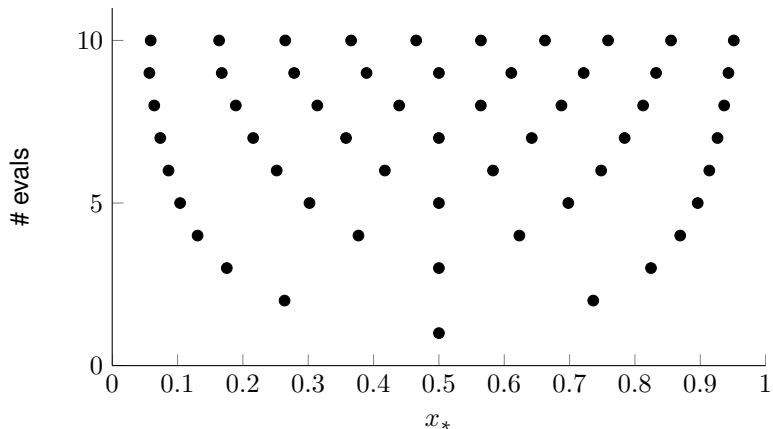
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- ▶ study how uncertainty drops from evaluation at x
- ▶ find x minimizing expected square error
- ▶ optimal location depends on # of evaluations (and kernel!)
- ▶ aka [Bayesian Quadrature](#) (see e.g. Osborne et al., NIPS 2012)

...but Numerical Analysis is not Machine Learning

some observations

Probability Theory can help Numerics ...

- ▶ understand implicit assumptions
- ▶ improve, generalise, invent new algorithms

...but Numerics has unique requirements

- ▶ computational cost
- ▶ robustness

let's discuss what either field can give the other

Schedule

NIPS 2012 workshop on probabilistic numerics

07:45 Matthias Seeger

PASCAL2 invited talk

08:15 Jacek Gondzio

PASCAL2 invited talk

08:55 Coffee Break

09:30 David Duvenaud

10:00 Spotlights

10:10 Posters & Discussion

16:00 Persi Diaconis

PASCAL2 invited talk

16:45 Ben Calderhead

PASCAL2 invited talk

17:15 Coffee Break

18:00 Ulrich Paquet (canceled) ← Philipp Hennig

18:30 Panel Discussion

19:00 End