Bayesian optimisation

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Problem statement

$$x^* = \arg\max_x f(x)$$

Constraints:

- f is a black box for which no closed form is known;
  - gradients $\frac{df}{dx}$ are not available.
- f is expensive to evaluate;
- (optional) uncertainty on observations y_i of f
  - e.g., $y_i = f(x_i) + \epsilon_i$ because of Poisson fluctuations.

Goal: find x^*, while minimizing the number of evaluations $f(x)$.

Disclaimer

If you do not have these constraints, there is certainly a better optimisation algorithm than Bayesian optimisation.

(e.g., L-BFGS-B, Powell's method (as in Minuit), etc)

Bayesian optimisation

for $t = 1 : T$,

1. Given observations (x_i, y_i) for $i = 1 : t$, build a probabilistic model for the objective f;

2. Compute the posterior predictive distribution;
   - Integrate out all possible true functions, using Gaussian process regression.

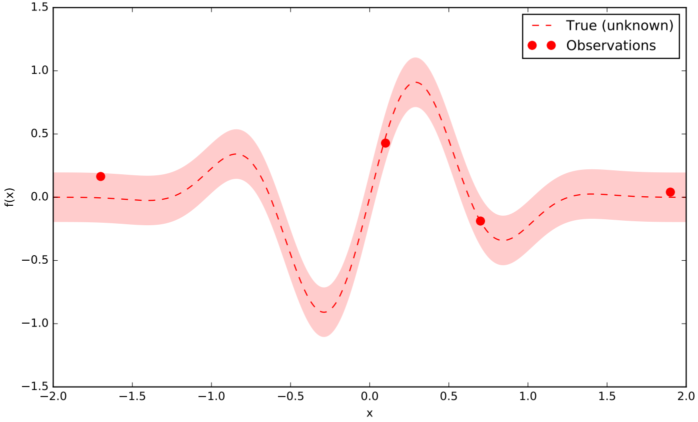
3. Optimise a cheap utility function u based on the posterior for sampling the next point.

$$x_{t+1} = \arg\max_x u(x)$$

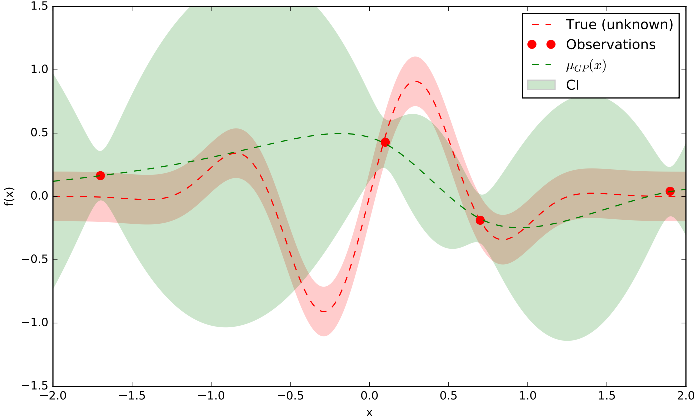
   Exploit uncertainty to balance exploration against exploitation.

4. Sample the next observation y_{t+1} at x_{t+1}.

Where shall we sample next?



Build a probabilistic model for the objective function



This gives a posterior distribution over functions that could have generated the observed data.

Acquisition functions

Acquisition functions $\mathrm{u}(x)$ specify which sample x should be tried next:

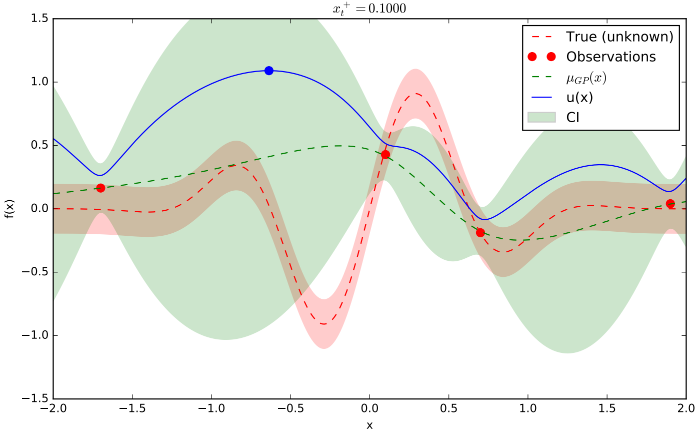
- Upper confidence bound $\mathrm{UCB}(x) = \mu_{GP}(x) + \kappa\sigma_{GP}(x)$;
- Probability of improvement $\mathrm{PI}(x) = P(f(x) \geq f(x_t^+) + \kappa)$;
- Expected improvement $\mathrm{EI}(x) = \mathbb{E}[f(x) - f(x_t^+)]$;
- ... and many others.

where x_t^+ is the best point observed so far.

In most cases, acquisition functions provide knobs (e.g., κ) for controlling the exploration-exploitation trade-off.

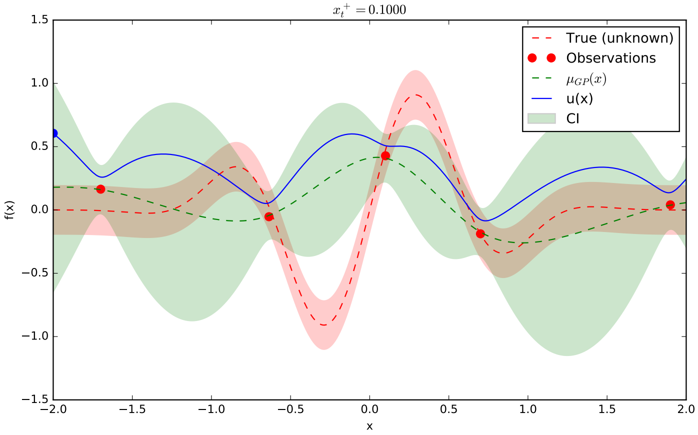
- Search in regions where $\mu_{GP}(x)$ is high (exploitation)
- Probe regions where uncertainty $\sigma_{GP}(x)$ is high (exploration)

Plugging everything together ($t = 0$)

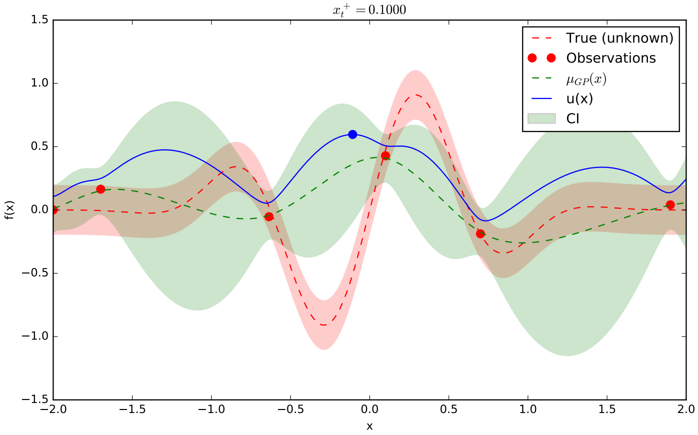


$$x_{t+1} = \arg\max_x \mathrm{UCB}(x)$$

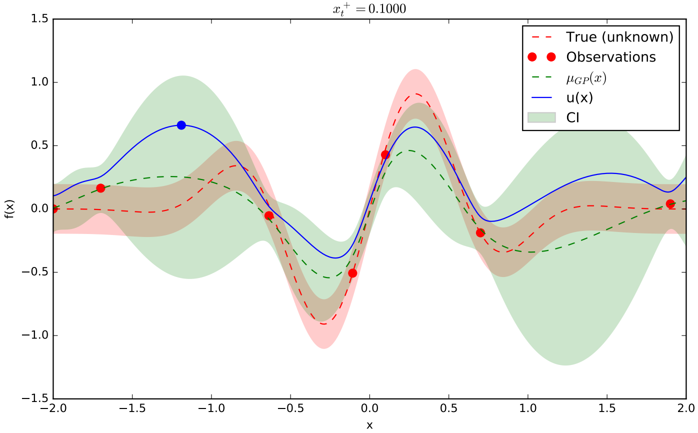
… and repeat until convergence ($t = 1$)



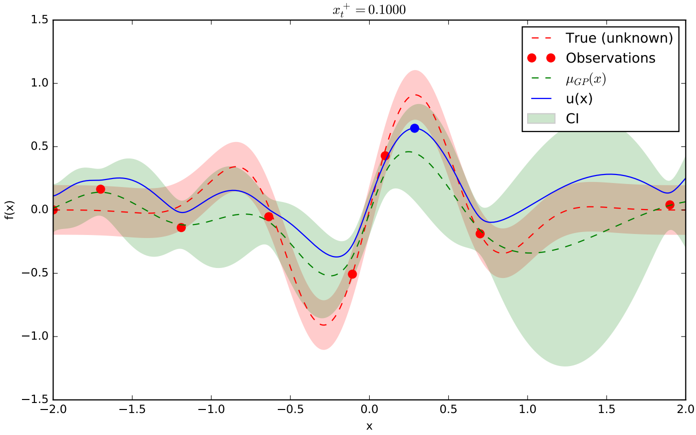
… and repeat until convergence ($t = 2$)



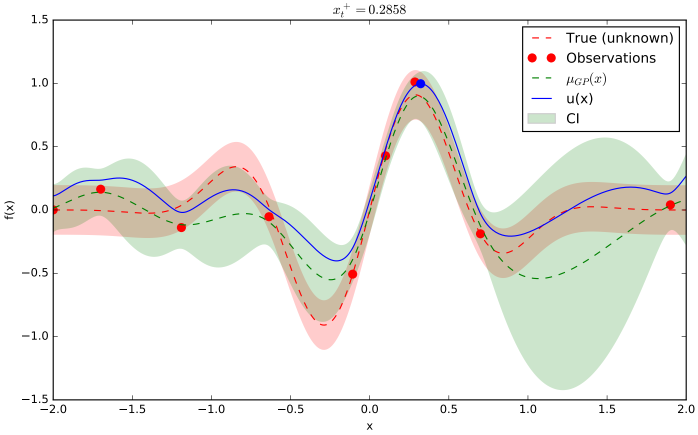
… and repeat until convergence ($t = 3$)



… and repeat until convergence ($t = 4$)



… and repeat until convergence ($t = 5$)



Limitations

- Bayesian optimisation has parameters itself!
  - Choice of the acquisition function
  - Choice of the kernel (i.e. design of the prior)
  - Parameter wrapping
  - Initialization scheme

- Gaussian processes usually do not scale well to many observations and to high-dimensional data.
  - Sequential model-based optimization provides a direct and effective alternative (i.e., replace GPs by a tree-based model).

Applications

- Bayesian optimization has been used in many scientific fields, including robotics, machine learning or life sciences.

- Use cases for high energy physics?
  - Optimisation of simulation parameters in event generators;
  - Optimisation of compiler flags to maximize execution speed;
  - Optimisation of hyper-parameters in machine learning for HEP;
  - ... let's discuss further ideas?

Software

- Python
  - Spearmint https://github.com/JasperSnoek/spearmint
  - GPyOpt https://github.com/SheffieldML/GPyOpt
  - RoBO https://github.com/automl/RoBO
  - scikit-optimize https://github.com/MechCoder/scikit-optimize (work in progress)
- C++
  - MOE https://github.com/yelp/MOE

Summary

- Bayesian optimisation provides a principled approach for optimising an expensive function f;
- Often very effective, provided it is itself properly configured;
- Hot topic in machine learning research. Expect quick improvements!

References

Brochu, E., Cora, V. M., and De Freitas, N. (2010). A tutorial on bayesian optimization of expensive cost functions, with application to active user modeling and hierarchical reinforcement learning. *arXiv preprint arXiv:1012.2599*.

Shahriari, B., Swersky, K., Wang, Z., Adams, R. P., and de Freitas, N. (2016). Taking the human out of the loop: A review of bayesian optimization. *Proceedings of the IEEE*, 104(1):148–175.