

# 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;
- uncertainty on observations  $y_i$  of  $f$  (i.e.,  $y_i = f(x_i) + \epsilon_i$ ).

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  $t = 1 : T$ ,

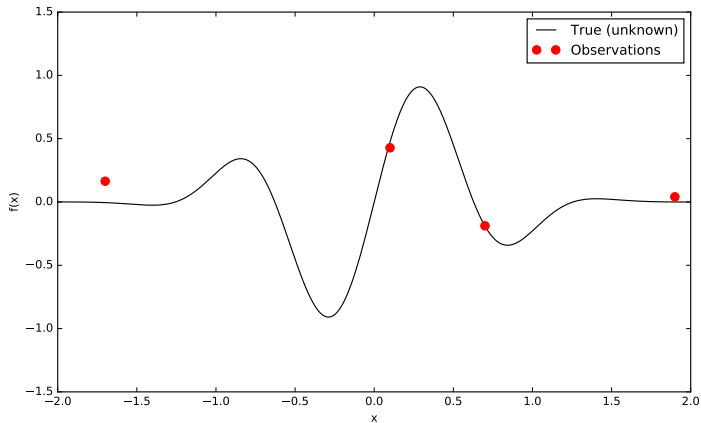
1. Given observations  $(x_i, y_i)$  for  $i = 1 : t$ , build a probabilistic model for the objective  $f$ ;
2. Compute the posterior predictive distribution;
  - Integrate out all possible true functions, using Gaussian process regression.
3. Optimise a cheap utility function  $u$  based on the posterior for sampling the next point.

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

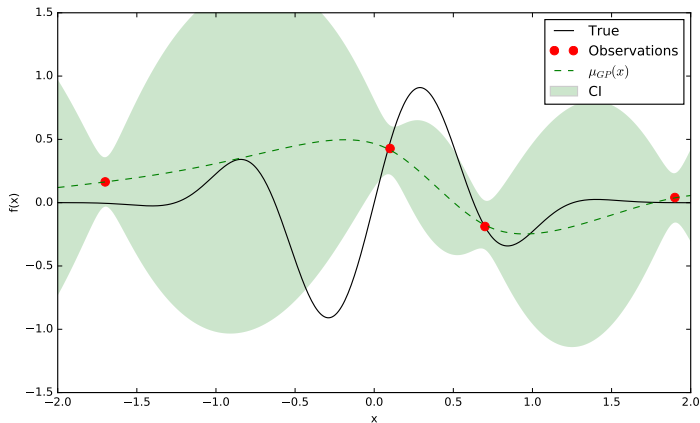
Exploit uncertainty to balance exploration against exploitation.

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  $u(x)$  specify which sample  $x$  should be tried next:

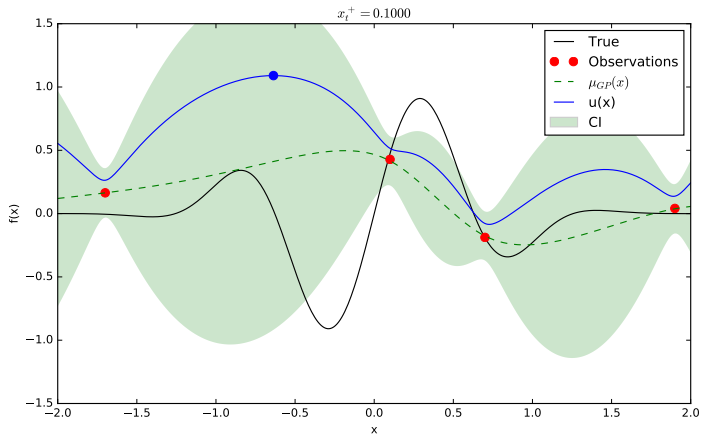
- Upper confidence bound  $UCB(x) = \mu_{GP}(x) + \kappa\sigma_{GP}(x)$ ;
- Probability of improvement  $PI(x) = P(f(x) \geq f(x_t^+) + \kappa)$ ;
- Expected improvement  $EI(x) = \mathbb{E}[f(x) - f(x_t^+)]$ ;
- ... and many others.

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

In most cases, acquisition functions provide knobs (e.g.,  $\kappa$ ) 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)

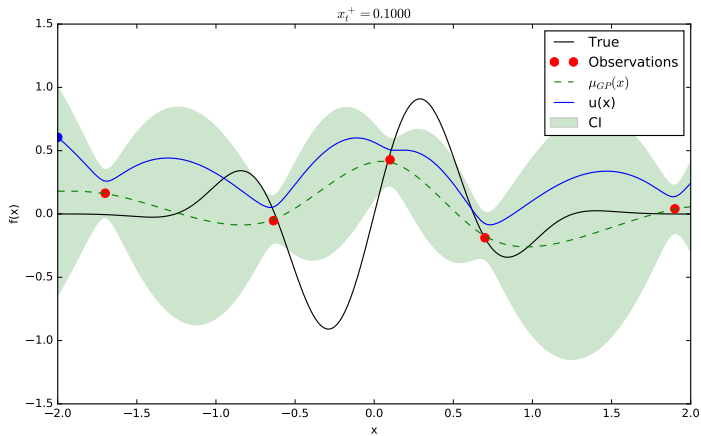
## Plugging everything together ( $t = 0$ )



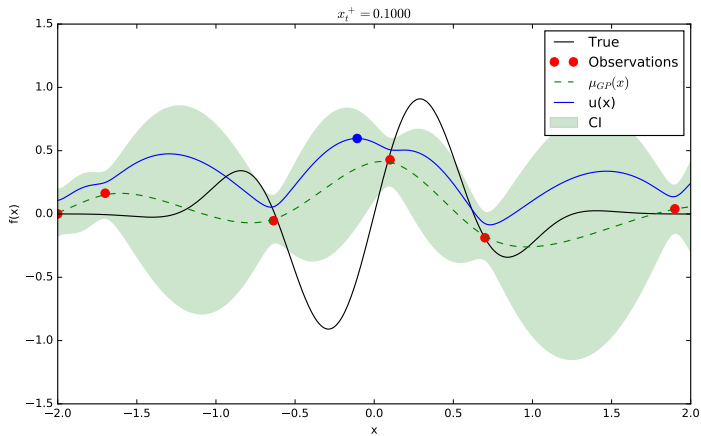
$$x_{t+1} = \arg \max_x \text{UCB}(x)$$



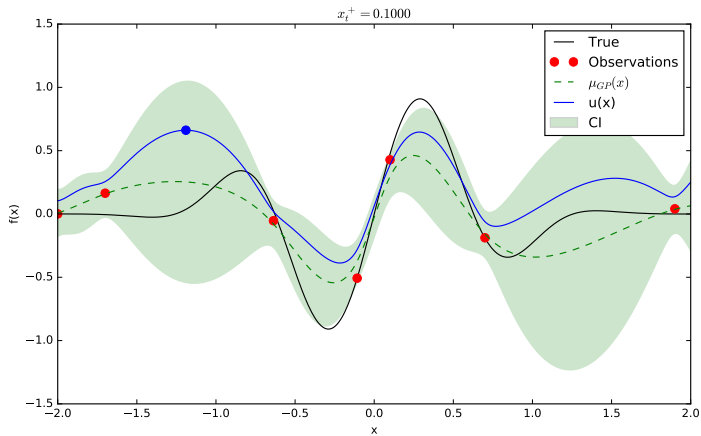
... and repeat until convergence ( $t = 1$ )



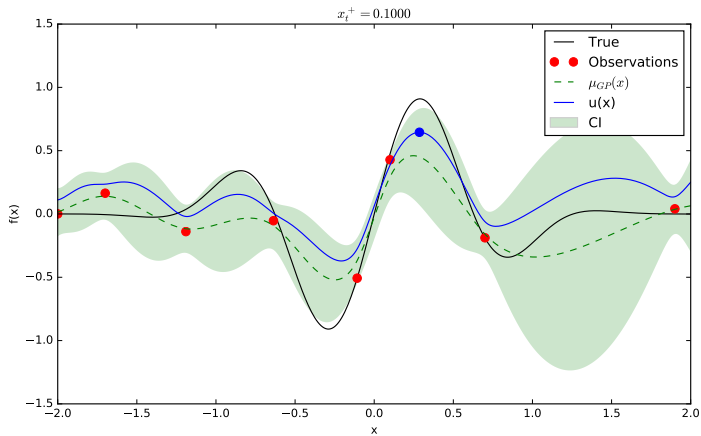
... and repeat until convergence ( $t = 2$ )



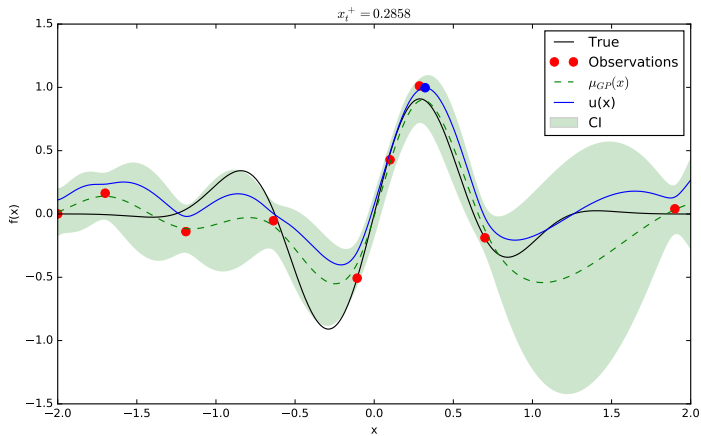
... and repeat until convergence ( $t = 3$ )



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



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



# Limitations

- Bayesian optimisation has parameters itself!
  - Choice of the 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
  - Spearmin <https://github.com/JasperSnoek/spearmin>
  - 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.