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).

Bayesian optimisation

for t = 1 : T,

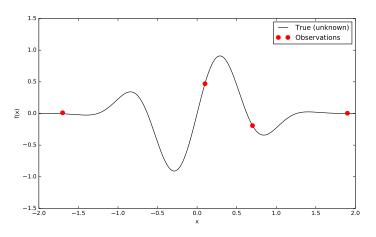
- 1. Given observations (x_i, y_i) for i = 1 : t, build a probabilistic model for the objective f;
- 2. Compute the posterior predictive distribution;
 - Integrate out all possible true functions, using Gaussian process regression.
- 3. Optimise a cheap utility function *u* for sampling the next point.

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

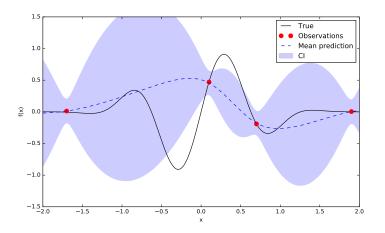
Exploit uncertainty to balance exploration against exploitation.

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

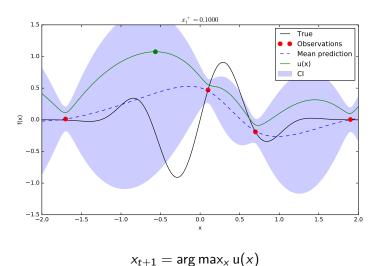
Acquisition functions u(x) specify which sample x should be tried next:

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

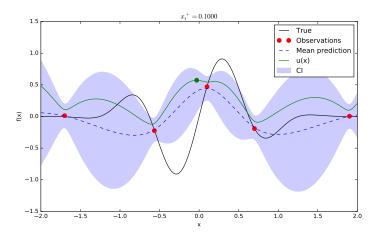
where x_t^+ is the best point observed so far.

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

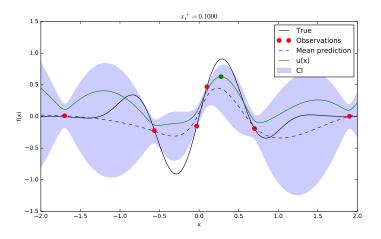
Plugging everything together (t = 0)



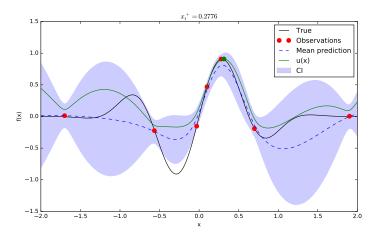
... and repeat until convergence (t = 1)



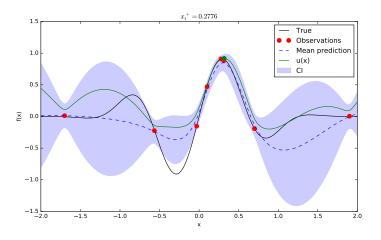
... and repeat until convergence (t = 2)



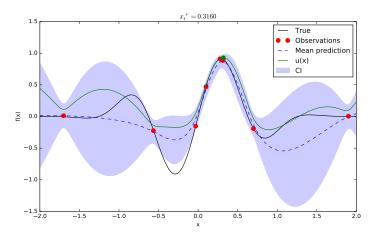
... and repeat until convergence (t = 3)



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



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



Applications in HEP?

Summary