Surrogate-Based Optimization of Stellarators

David Bindel   Silke Glas

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Department of Computer Science
Cornell University

Who?

Simons Collaboration: “Hidden Symmetries and Fusion Energy”

`https://hiddensymmetries.princeton.edu/`

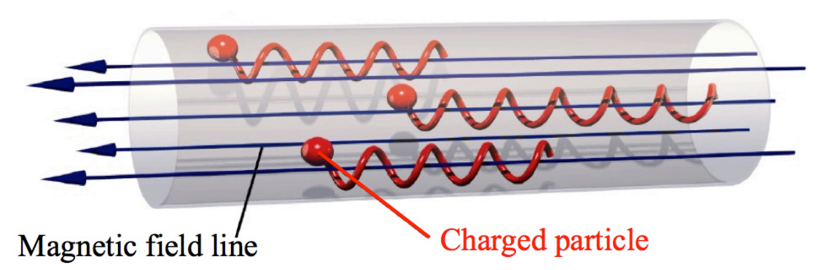
Princeton, NYU, Maryland, IPP Greifswald, Warwick, CU Boulder, UW Madison, EPFL, ANU, UT Austin, U Arizona.

Cornell group:

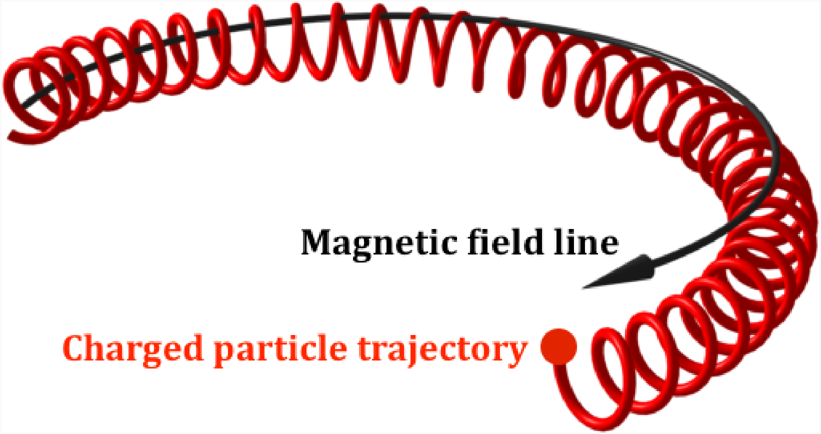
- Silke Glas (Simons postdoc)
- Misha Padidar (CAM PhD student)
- Ariel Kellison (CS PhD student)
- Nick Parrilla (predoc student)
- Paco Rilloraza (ugrad student)

with involvement from many others.

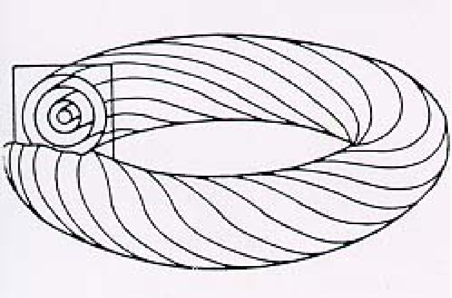
Magnetic confinement basics

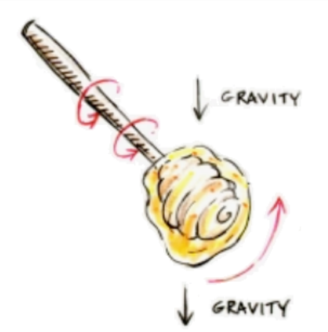


Magnetic confinement basics



Magnetic confinement basics

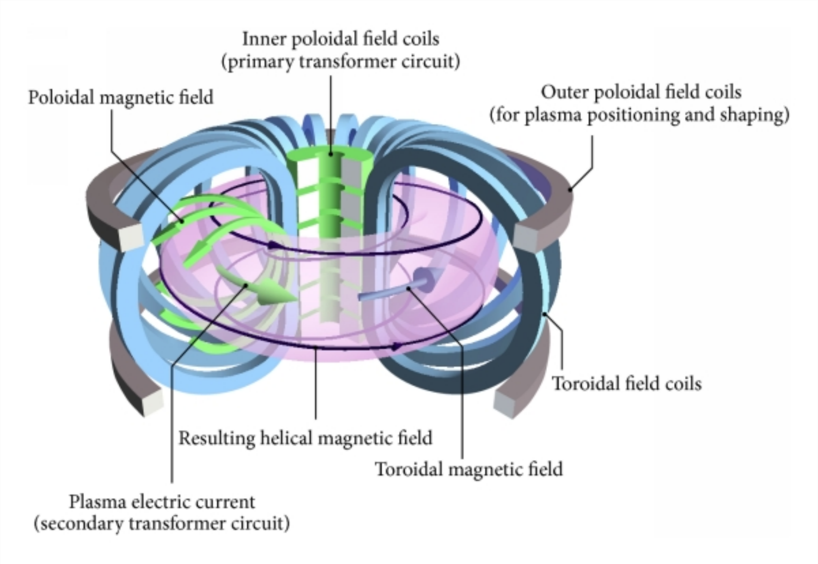




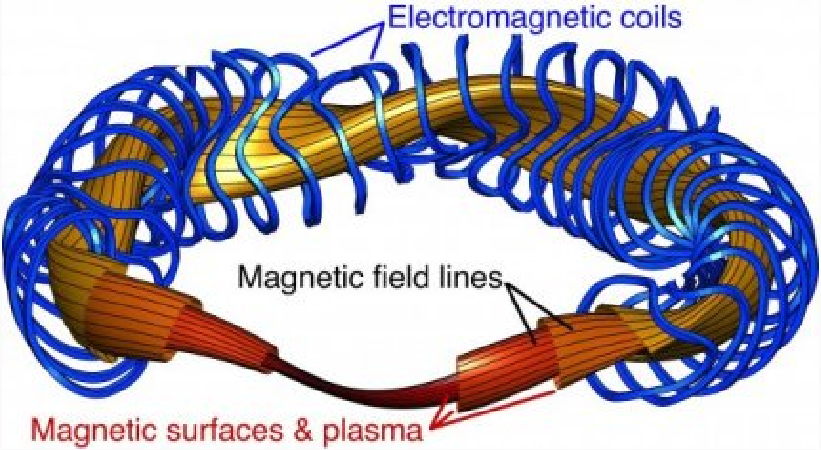
- Particles confined to magnetic surfaces (invariant tori).
- Drift cancels over the full trajectory.

(V. I. Arnold, *Small denominators and problems of stability of motion in classical and celestial mechanics*, Russ. Math. Surv., 1963.)

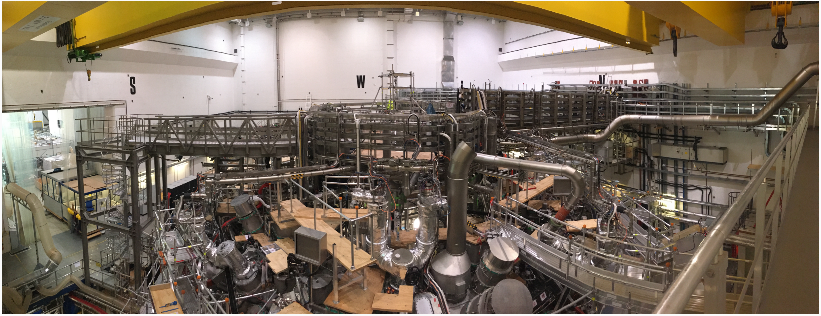
The big name: Tokamaks



Stellarator Concept



Wendelstein 7-X Machine



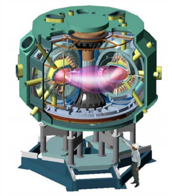
Operating since 2015-12-10;
plasma discharges lasting up to 30 min.

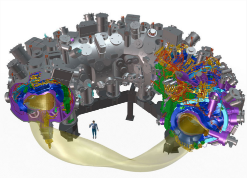
Optimization Under Uncertainty

Low construction tolerances:

- NCSX: 0.08%
- Wendelstein 7-X: 0.1% – 0.17%

Higher tolerances as coil opt goal!

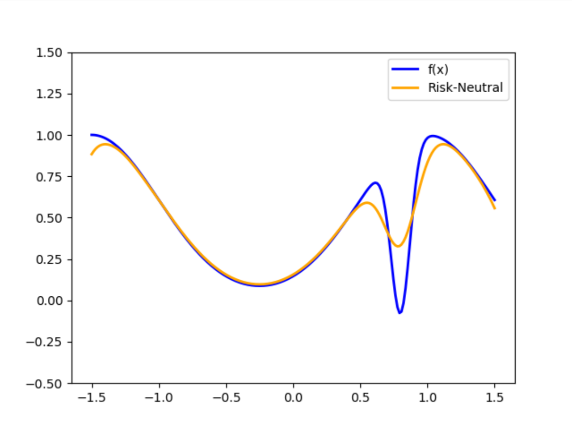




Also want tolerance to

- Changes to control parameters
- Uncertainty in physics or model

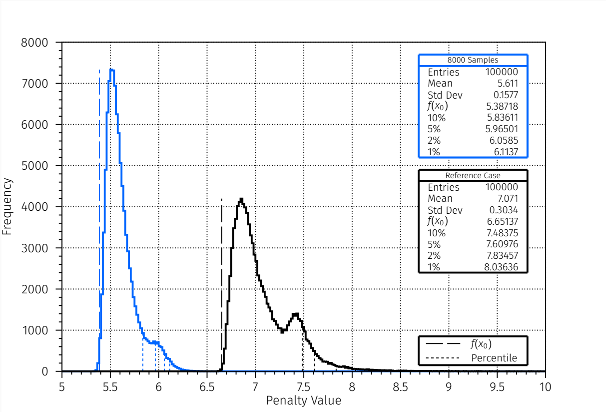
Risk-neutral OUU



Want efficient OUU in ~ 200 dimensions

$$\min_{x \in \Omega} \mathbb{E}_U[f(x - U)]$$

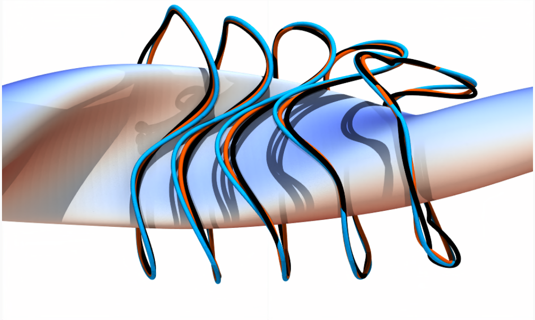
(Recent) Prior: Monte Carlo Approach



Robustness & mean perf greatly improved (w/ $\sim 10^8$ evals)

J.-F. Lobsien, M. Drevlak, T. Kruger, S. Lazerson, C. Zhu, T. S. Pedersen, *Improved performance of stellarator coil design optimization*, Journal of Plasma Physics, 2020.

Our Approach: fast TuRBO-ADAM



Black: ref; red: TuRBO-ADAM 10mm; blue: TuRBO-ADAM 20mm.

Evaluate objective with FOCUS from PPPL.

- Global search with modified TuRBO
- Local refinement with ADAM with control variate

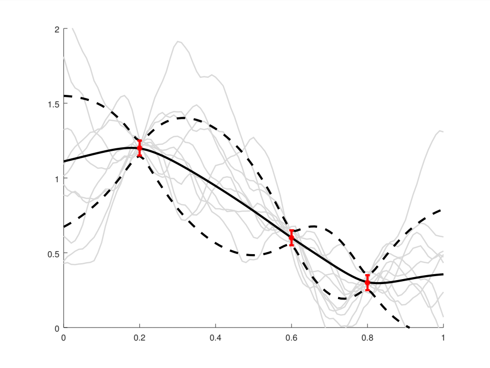
Costs about 0.01% the evaluation budget.

Global search: TuRBO for OUU

Combine two ideas:

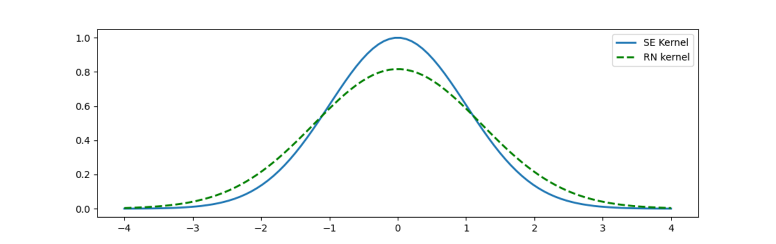
- TuRBO: Trust-Region Bayesian Optimization (Eriksson, Pearce, Gardner, Turner, Poloczek, 2019)
- BO under uncertainty (Beland and Nair, 2017)

TuRBO idea



- Do a rough global sampling at M points.
- Local Gaussian process models of f near each point.
- Thompson sampling to choose which local model (and trust region) to refine next.

OUU adaptation



- TuRBO builds GP models for $f(x)$ (nominal objective)
- Simple transform from GP for $f(x)$ to GP for $E_U[f(x+U)]$

ADAM + control variates

- Regular ADAM: stochastic gradient algorithm based on

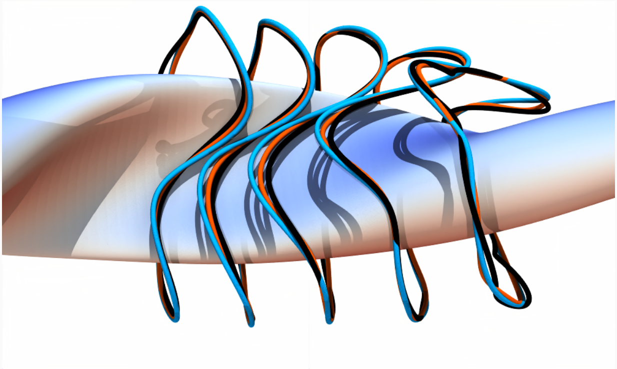
$$g(x) = \nabla f(x + U)$$

  for a random draw U (can also do mini-batch).
- Variance reduction with control variates (Wang, Chen, Smola, Xing, 2013)

$$\begin{aligned} g(x) &= \nabla f(x + U) + \alpha(\hat{g}(x) - E[\hat{g}(x)]) \\ \hat{g}(x) &= \nabla f(x) + HU. \end{aligned}$$

- True Hessian not avail, so set H to be an approximate Hessian (BFGS approximation via gradients from ADAM).

And more!



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(Look at 2019 annual meeting for more talks!)