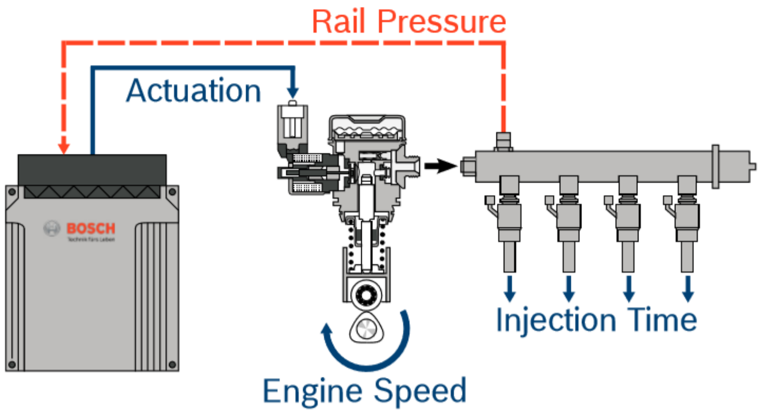
Safe Bayesian Optimization for Optimal Control



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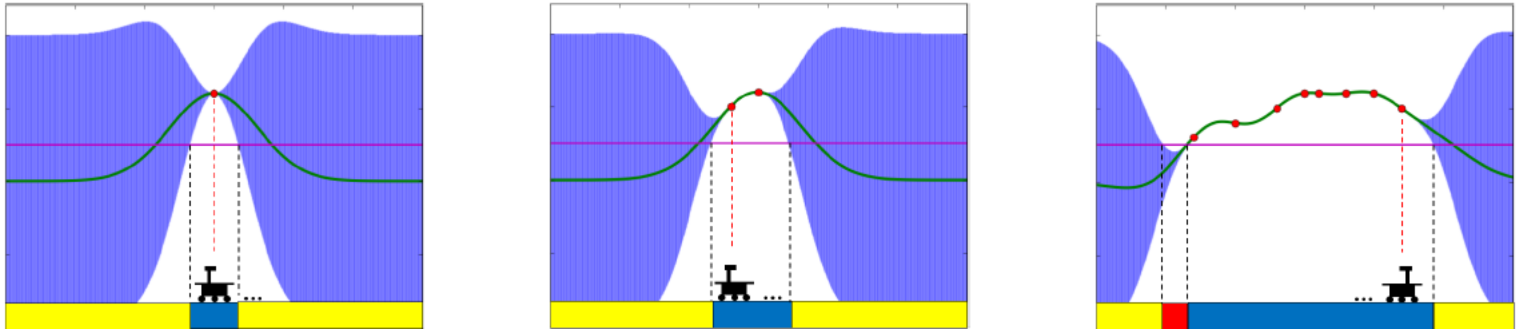
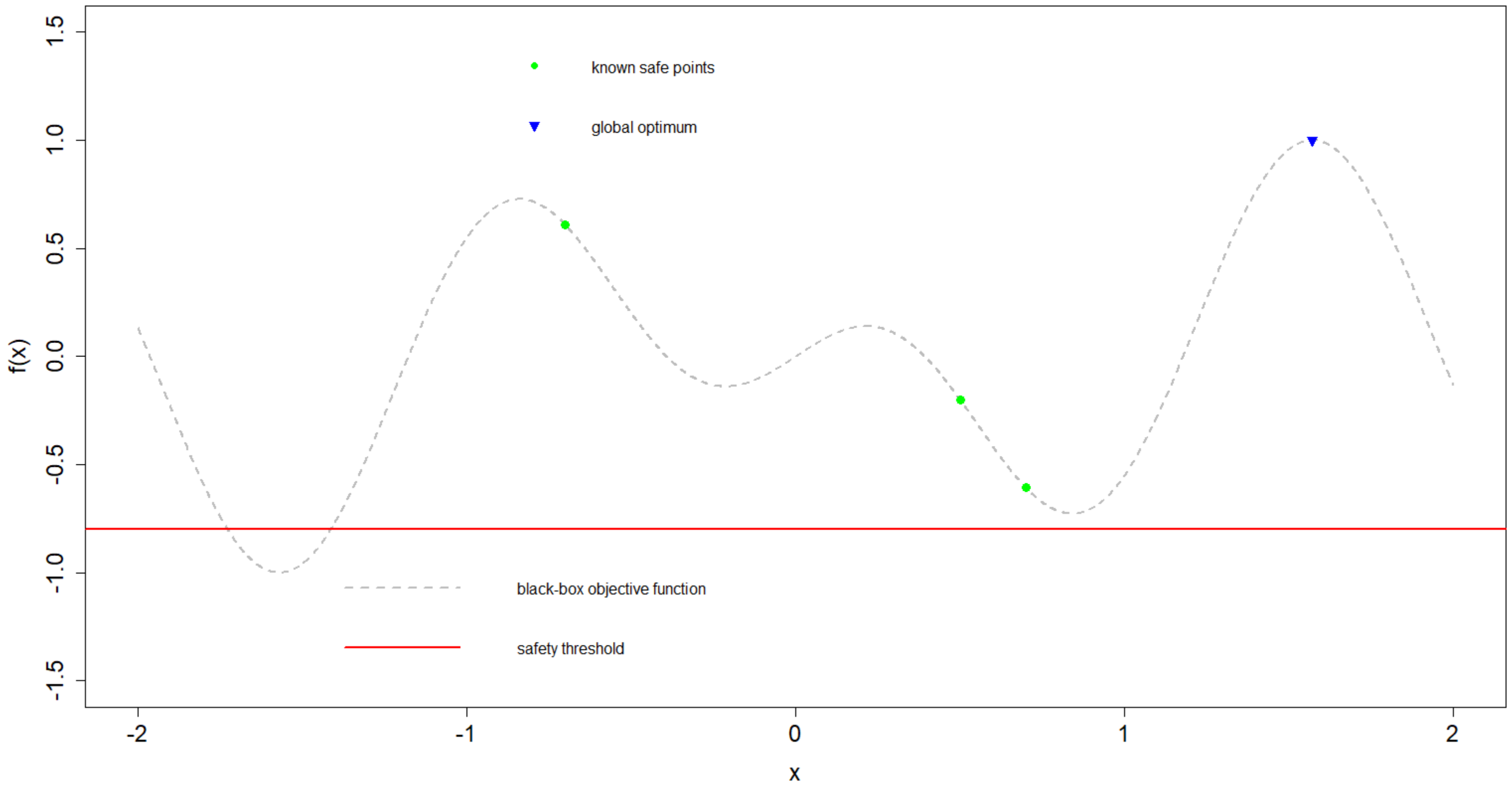
Sui, Y., Gotovos, A., Burdick, J., & Krause, A. (2015, June). Safe exploration for optimization with Gaussian Processes. In *International Conference on Machine Learning* (pp. 997-1005).



Wachi, A., Sui, Y., Yue, Y., & Ono, M. (2018). Safe Exploration and Optimization of Constrained MDPs using Gaussian Processes. In AAAI Conference on Artificial Intelligence (AAAI).

Safety concept

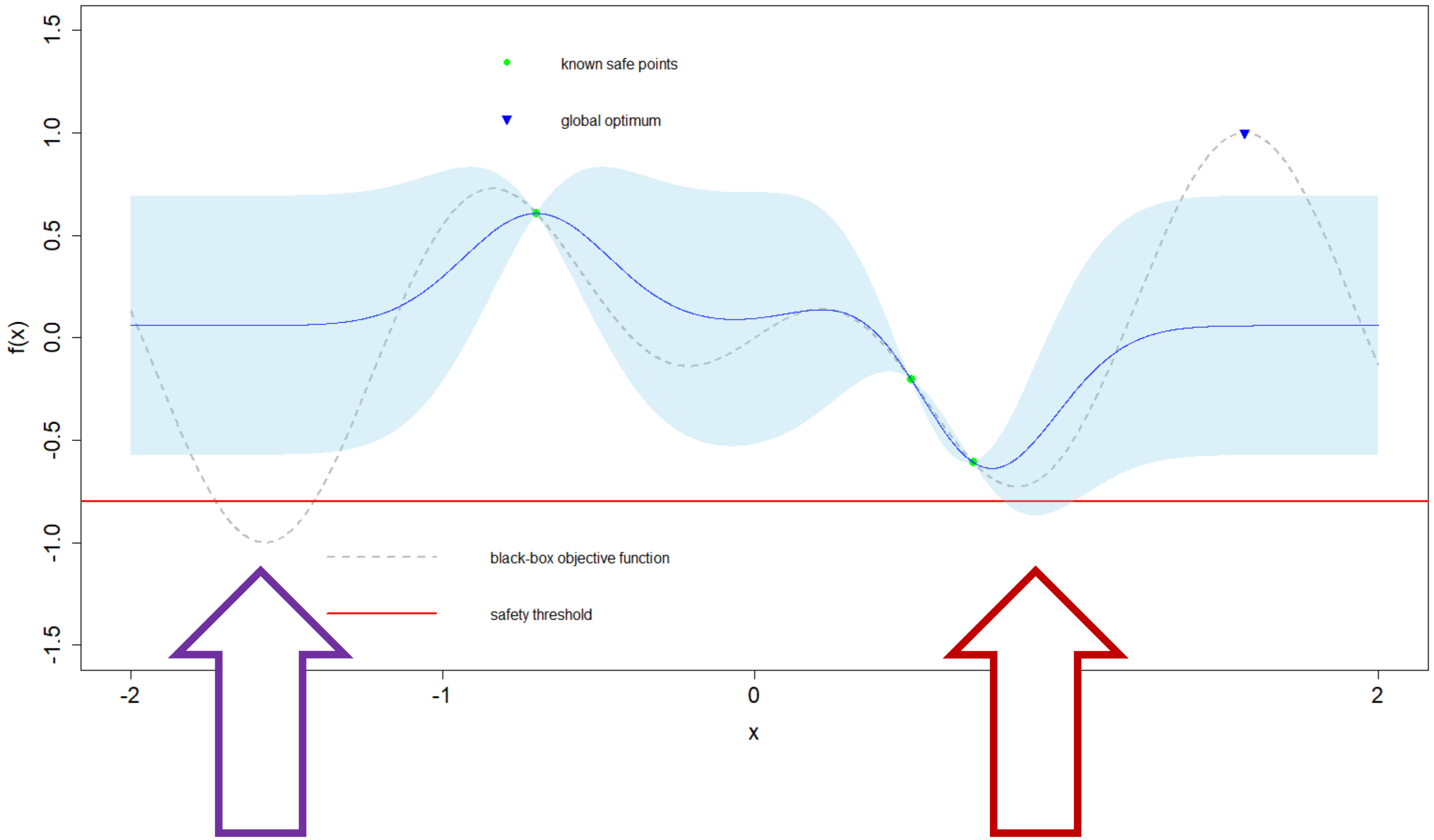
- ❑ Starting from some initial safe points (e.g. machinery settings):
  - ❑ Search for the optimum (e.g. maximum of some KPI) …
  - ❑ … avoiding to violate a given (safety) threshold (e.g. a minimum performance level)

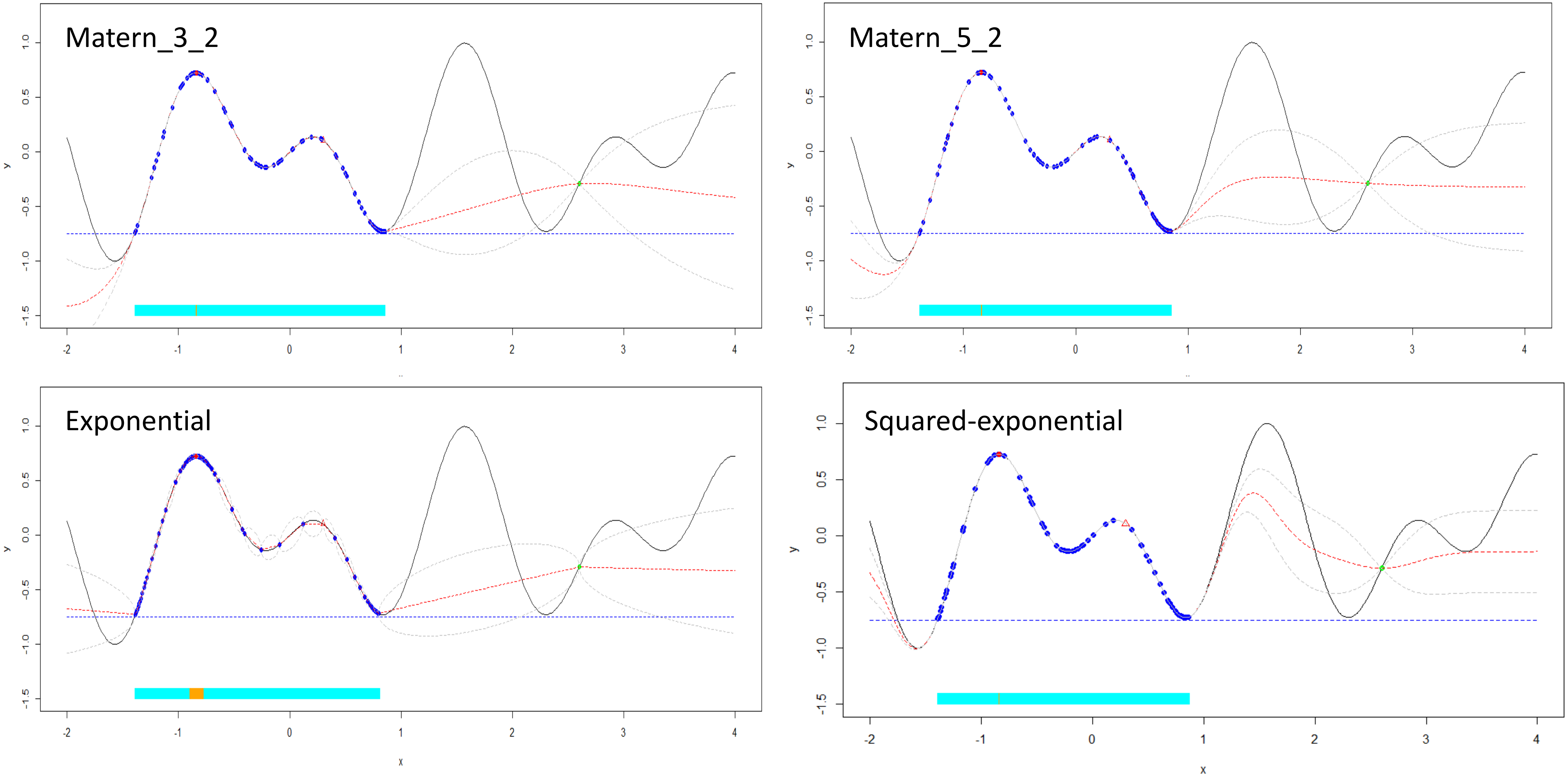


Safety concept

- Use a probabilistic model of the objective function to:
  - Expand «safe region» <u>safely</u>
  - While searching for the optimum

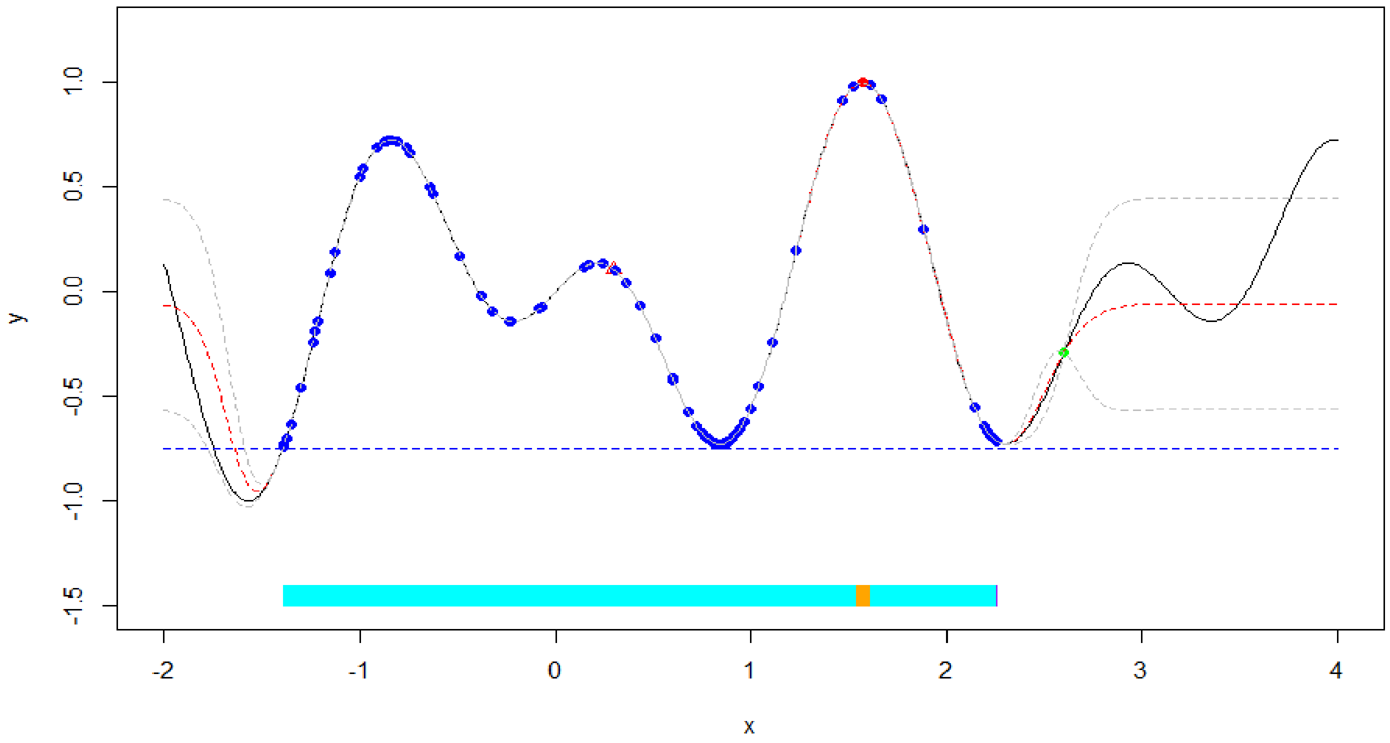
- Parameters of the probabilitic model have to be set up properly, otherwise:
  - We might violate the safety threshold
  - We could be unable to expand the safe region





Matern_3_2
Matern_5_2
Exponential
Squared-exponential
y
x
1.0
0.5
0.0
-0.5
-1.0
-1.5
-2
-1
0
1
2
3
4

Lipschitz-dependent Squared Exponential



- Most of the real world systems (e.g. industrial systems, are characterized by Lipschitz continuous objective functions)
- Knowledge about the Lipschitz constant allows for a proper set up of the probabilistic model (in particular its kernel aka covariance function)
- Lipschitz constant could be
  - known a priori (or at least a good estimation)
  - Inferred during the safe optimization process

Application domains

- Manufacturing processes
- Control of complex systems (e.g. water/energy/oil&gas supply networks)
- Design of experiments
- Clinical studies – therapy design