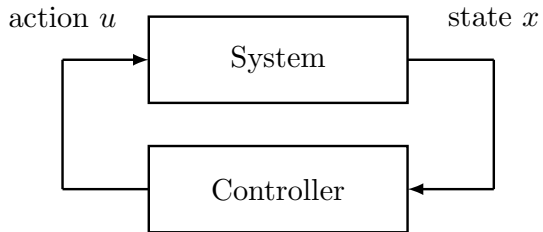
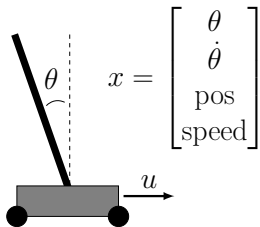


Previously on MLRG

Closed loop control



LQR

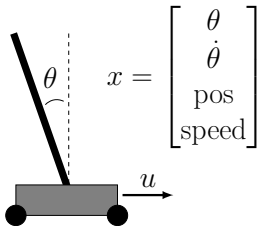


$$x' = Ax + Bu$$

↑ ↑
State Action

Physics

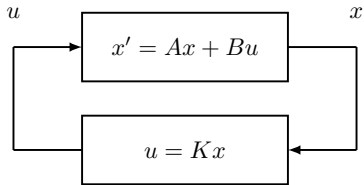
LQR



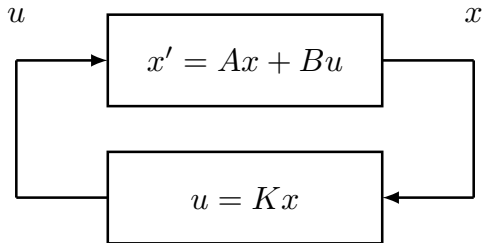
Physics

$$x' = Ax + Bu$$

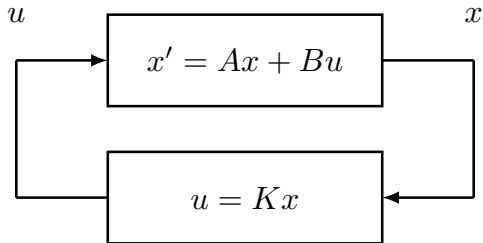
↑ ↑
State Action



Solving for K



Solving for K



$$J = \int (x - x^*)^\top Q (x - x^*) + u^\top R u \quad dt$$

Go to x^* min control
↓ ↓

Solving for K

$$J = \int (x - x^*)^\top Q (x - x^*) + u^\top R u \quad dt$$

Go to x^* min control
↓ ↓

Learning A, B

$$x' = Ax + Bu$$

Learning A, B

$$x' = Ax + Bu$$

$$\min_{A, B} \|Ax + Bu - x'\|$$

Learning A, B

$$x' = Ax + Bu$$

$$\min_{A, B} \|Ax + Bu - x'\|$$

Today

What if?

Today

What if?

- Nonlinear?
- Wrong model?

Today

What if?

- Nonlinear?
- Wrong model?

Today

What if?

- Nonlinear?
- Wrong model?

Today

What if?

- Nonlinear?
- Wrong model?
- Learning?
- Safety?

Today

What if?

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Today

What if?

- Nonlinear?
- Wrong model?
- Learning?
- Safety?

Today

LQR



Model Predictive Control



safe RL

Today

LQR



Model Predictive Control

↓ Nonlinear

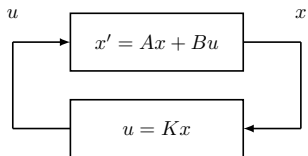
Learning ↓

↓ Explore/Exploit

Constraints ↓

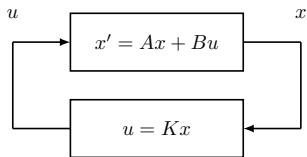
safe RL

LQR vs MPC

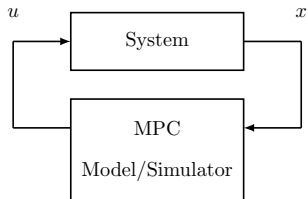


Find K a priori

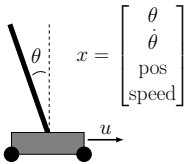
LQR vs MPC

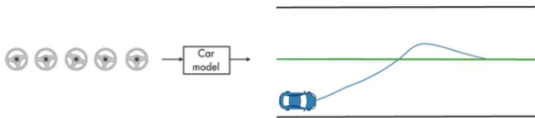
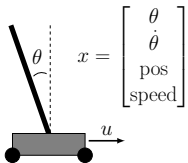


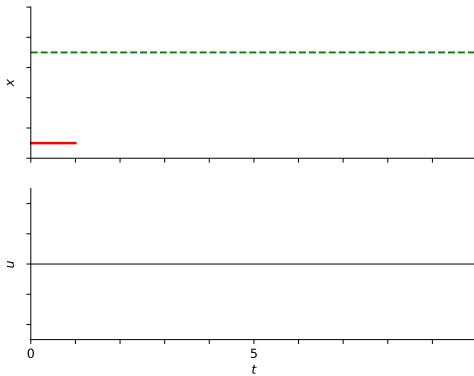
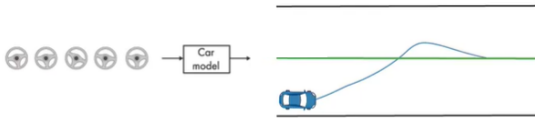
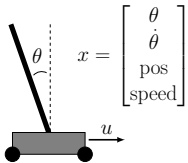
Find K a priori

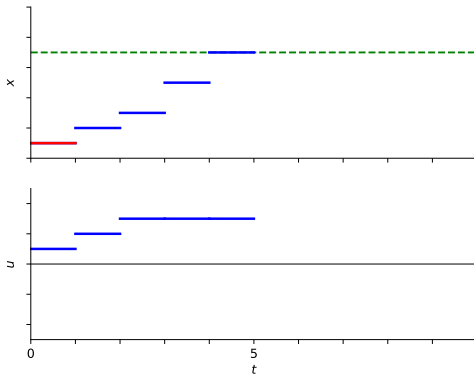
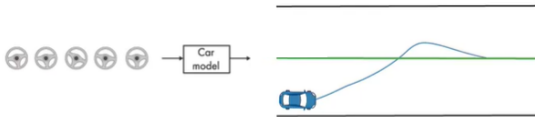
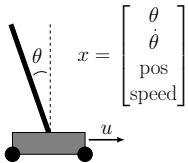


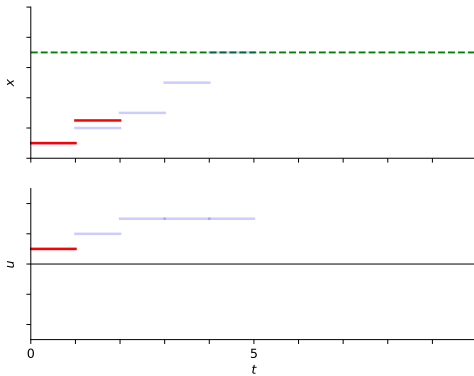
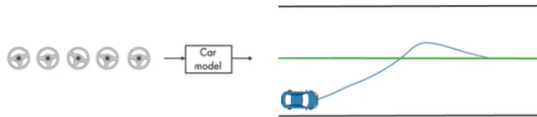
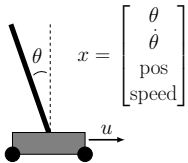
Find u at every step

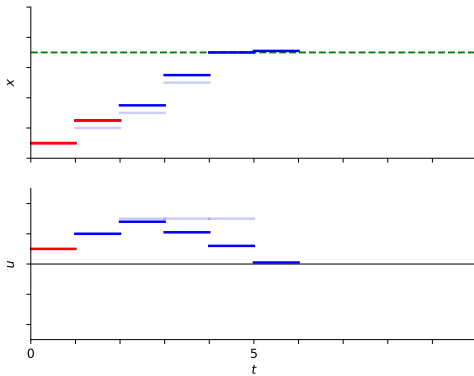
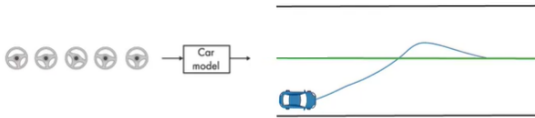
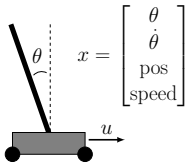


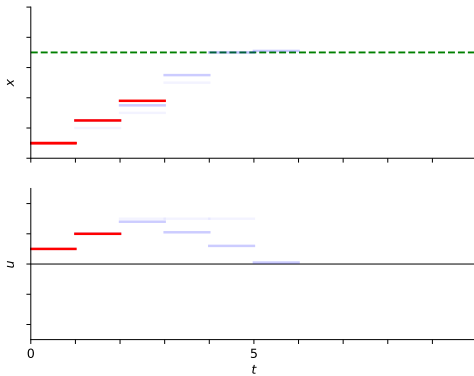
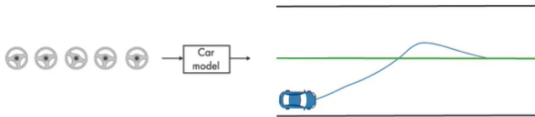
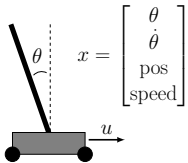


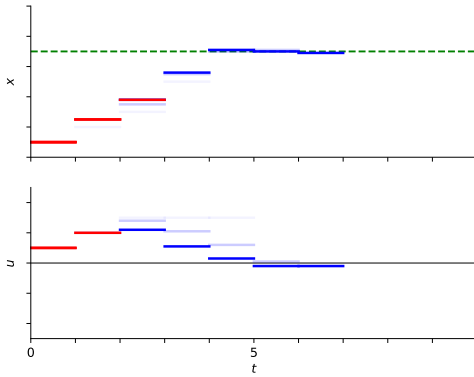
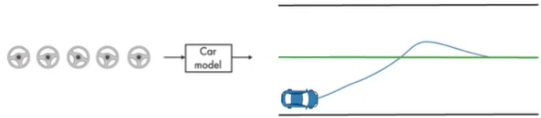
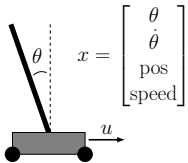












LQR vs MPC

Off/Online

Full/Local model

Non-linear

LQR vs MPC

Off/Online

Full/Local model

Non-linear

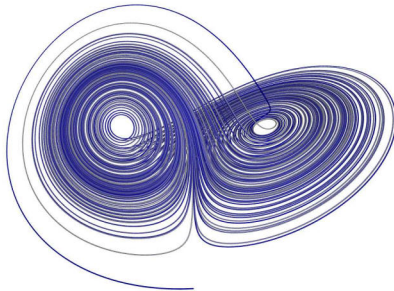


LQR vs MPC

Off/Online

Full/Local model

Non-linear



Example

$$x_{i+1} = A(x_t)x_i + B(x_t)u_i$$

Example

$$x_{i+1} = A(x_t)x_i + B(x_t)u_i$$

$$\begin{array}{ll} \min_{u_{t+1}, \dots, u_{t+H}} & \sum_{i=1}^H \dots \\ \text{s.t.} & x_{i+1} = A(x_t)x_i + B(x_t)u_i \end{array}$$

Example

$$x_{i+1} = A(x_t)x_i + B(x_t)u_i$$

$$\begin{aligned} \min_{u_{t+1}, \dots, u_{t+H}} \quad & \sum_{i=1}^H x_{t+i}^\top Q x_{t+i} + u_{t+i}^\top R u_{t+i} \\ \text{s.t.} \quad & x_{i+1} = A(x_t)x_i + B(x_t)u_i \end{aligned}$$

Example

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or

$$u_t = Kx_t$$

or

$$u_t, \dots, u_{t+H} = NN(x_t, \theta)$$

more flexible and hungry

MPC

Replace full planning by local optimization

Learning

“Online LQR”

Learning

“Online LQR”

True dynamics: $x' = Ax + Bu$

Model of the system: $x' = A_t x + B_t u$

Learning

“Online LQR”

True dynamics: $x' = Ax + Bu$

Model of the system: $x' = A_t x + B_t u$

Start with (A_0, B_0) , update as you go

Learning safely?

Safety

Correct models

Explore/Exploit

Uncertainty

Safety

Safety

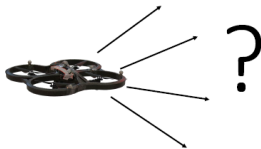
Safety

Ensure we don't crash

avoid known bad outcomes / stay within known safe regime

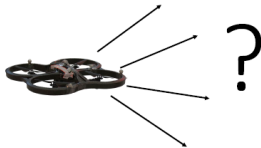
A safe starting point

Uncertainty about the dynamics



A safe starting point

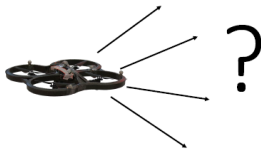
Uncertainty about the dynamics



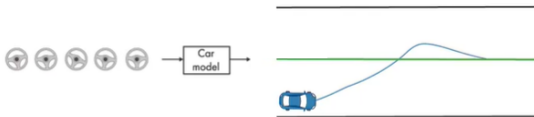
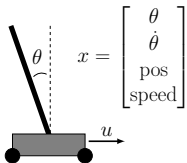
There is a safe controller that can take over if $x \in \mathcal{X}_{\text{safe}}$

A safe starting point

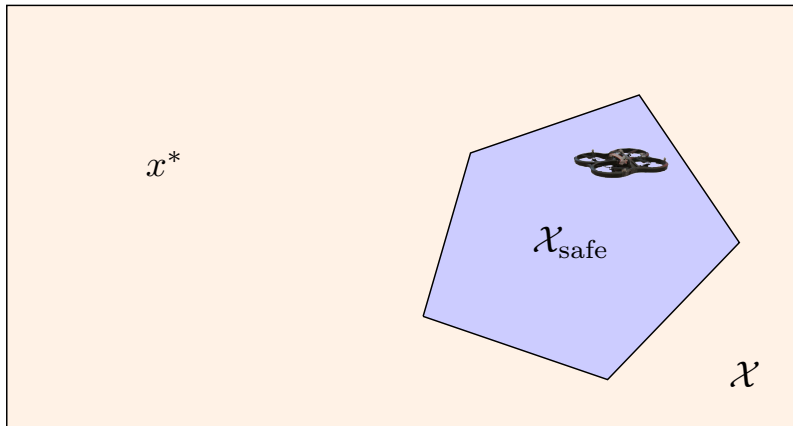
Uncertainty about the dynamics



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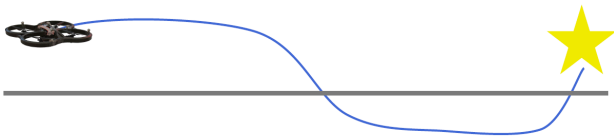


A safe starting point



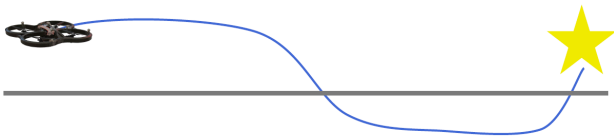
How do we get to x^* ?

Safety objectives



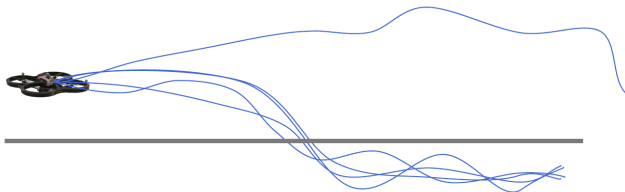
Safety objectives

$$\text{Loss} = J$$



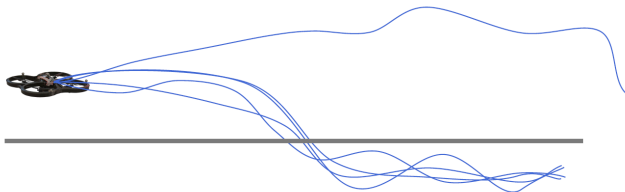
Safety objectives

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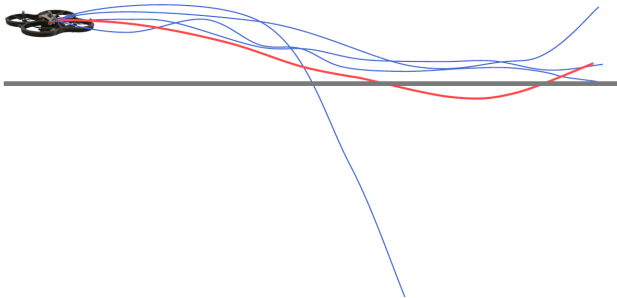
Safety objectives

$$\text{Loss} = \mathbb{E}[J]$$



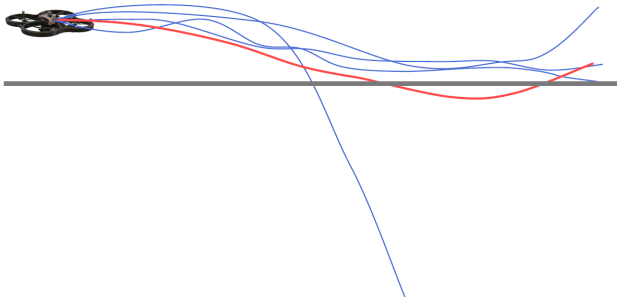
Safety objectives

$$\text{Loss} = \mathbb{E}[J]$$



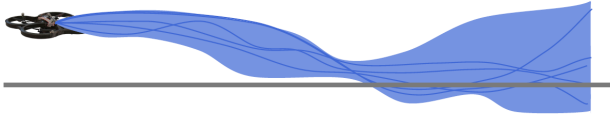
Safety objectives

$$\text{Loss} = \mathbb{E}[J] + \mathbb{E}[(J - \mathbb{E}[J])^2]$$



Safety objectives

Loss = $\mathbb{E}[J]$, but with safety constraints

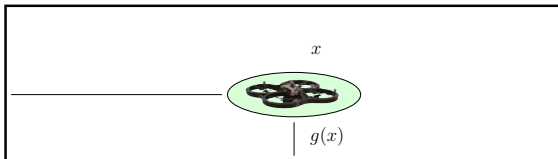


Safety constraints

Each step is optimization → constrained opt.

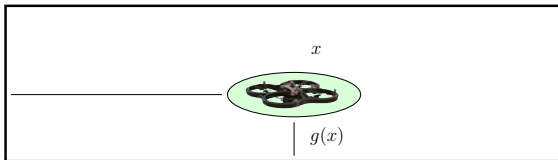
Safety constraints

Each step is optimization \rightarrow constrained opt.



Safety constraints

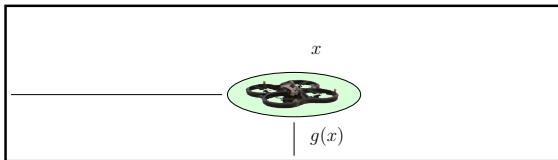
Each step is optimization \rightarrow constrained opt.



$$g(x) \geq 0$$

Safety constraints

Each step is optimization \rightarrow constrained opt.

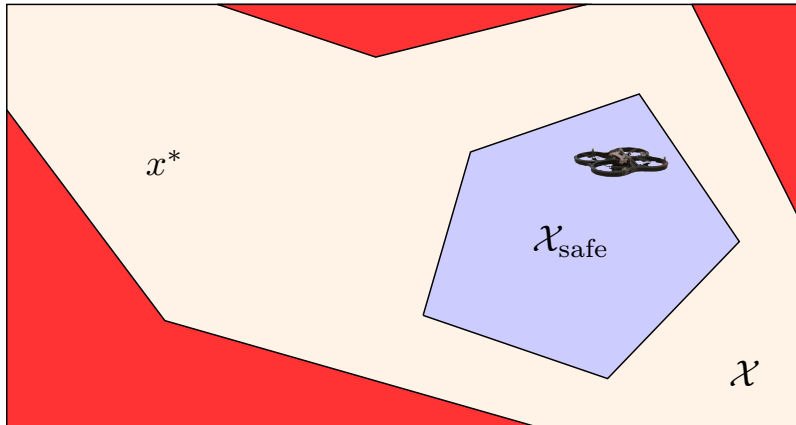


$$g(x) \geq 0$$

$$\theta \rightarrow u \rightarrow x$$

$$g(\theta) \geq 0$$

Safety constraints



How do we get to x^* ?

Uncertain transition dynamics

$$x' = f(x, u)$$

$$f(x, u) = h(x, u) + e(x, u)$$

h is known

e is not, but we have a probabilistic model

Uncertain transition dynamics

$$x' = f(x, u)$$

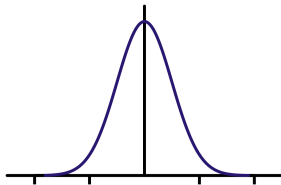
$$f(x, u) = h(x, u) + e(x, u)$$

h is known

e is not, but we have a probabilistic model

For (μ, σ) and β , with high probability

$$|\mu(x, u) - e(x, u)| \leq \beta\sigma(x, u)$$



Optimization with Uncertainty

Gaussian Processes Crash Course

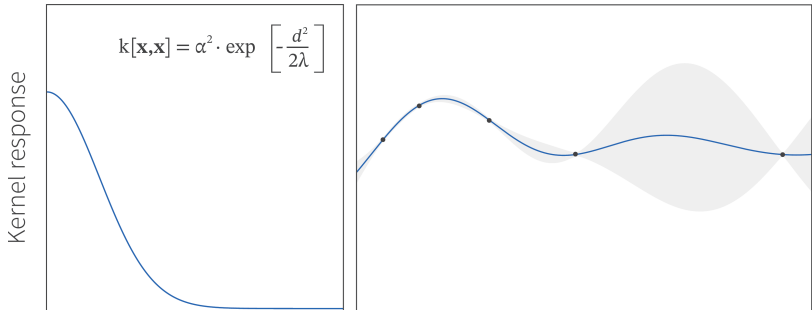
Kernel $k(x, y)$

Optimization with Uncertainty

Gaussian Processes Crash Course

Kernel $k(x, y)$

Squared exponential

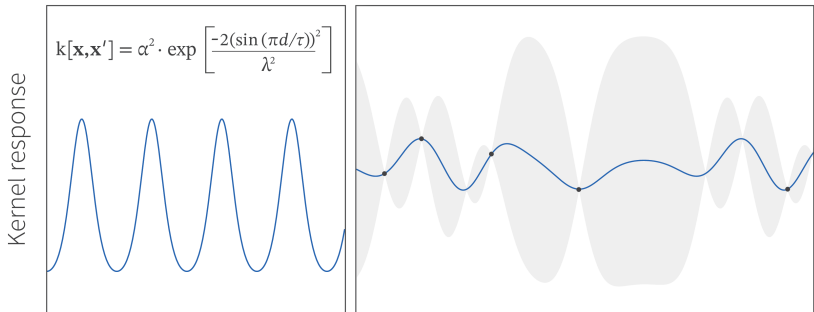


Optimization with Uncertainty

Gaussian Processes Crash Course

Kernel $k(x, y)$

Periodic

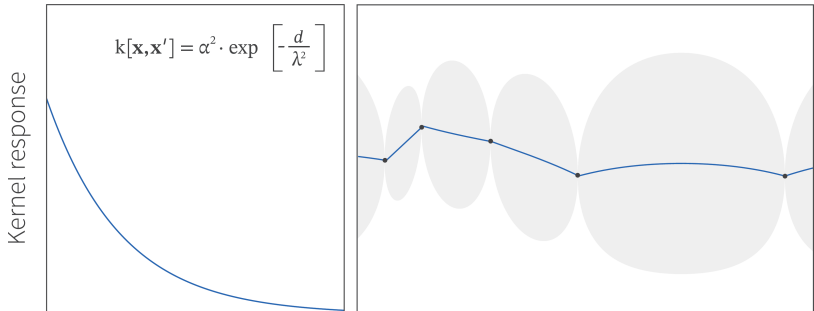


Optimization with Uncertainty

Gaussian Processes Crash Course

Kernel $k(x, y)$

Matérn 0.5



Optimization with Uncertainty

Gaussian Processes Crash Course

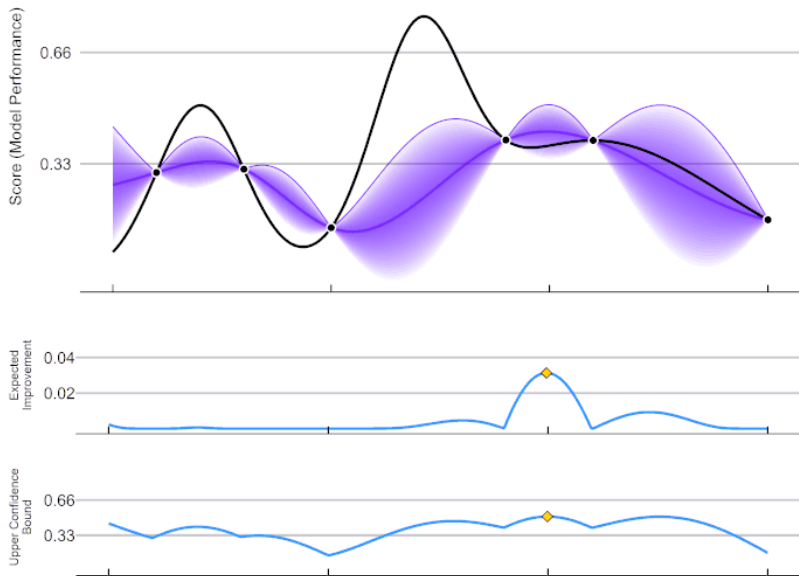
Kernel $k(x, y)$

Linear regression: $\|Xw - y\|^2$

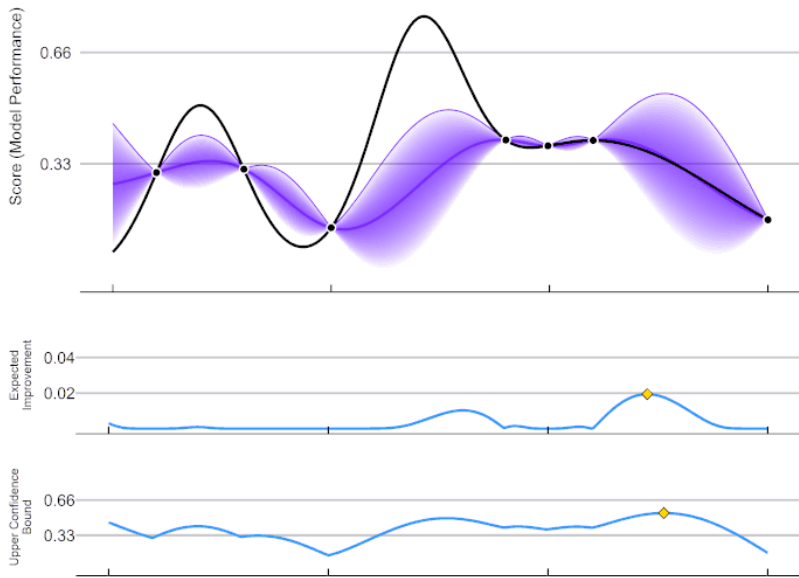
Kernel regression: $\|Kw - y\|^2$ where $K_{ij} = k(x_i, x_j)$

+ Covariances

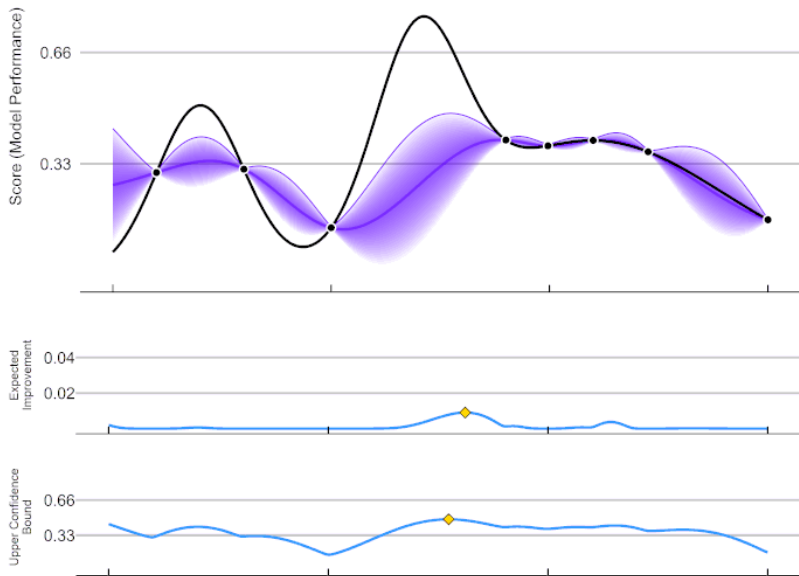
Exploration/Exploitation



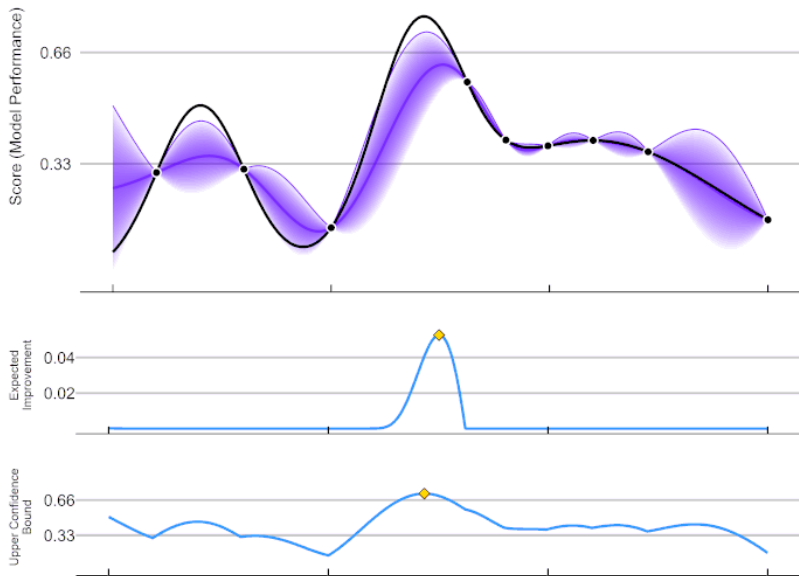
Exploration/Exploitation



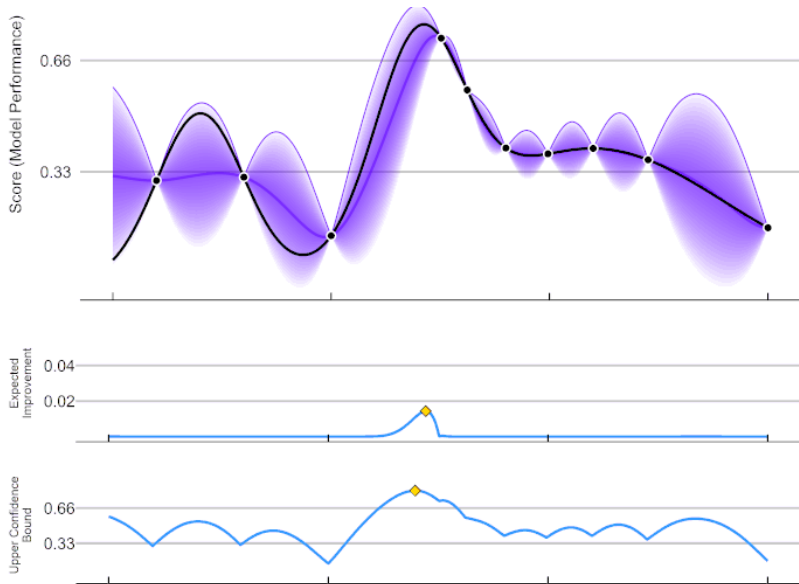
Exploration/Exploitation



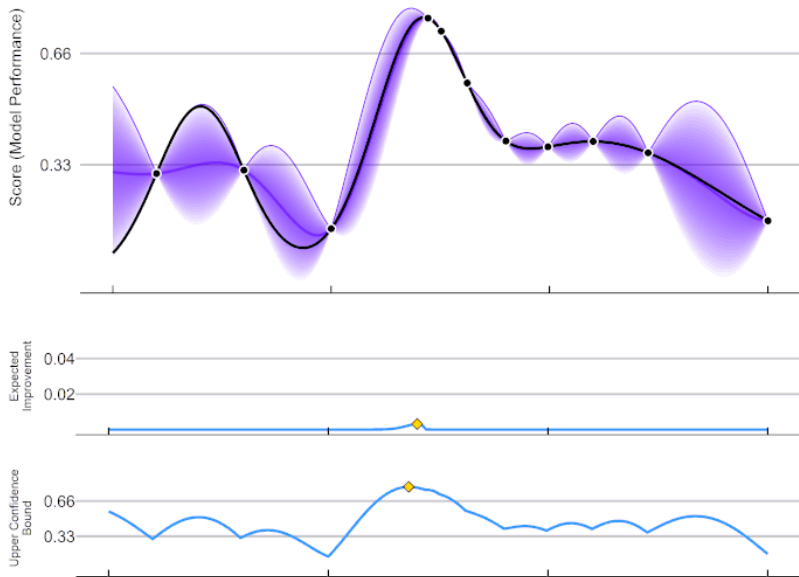
Exploration/Exploitation



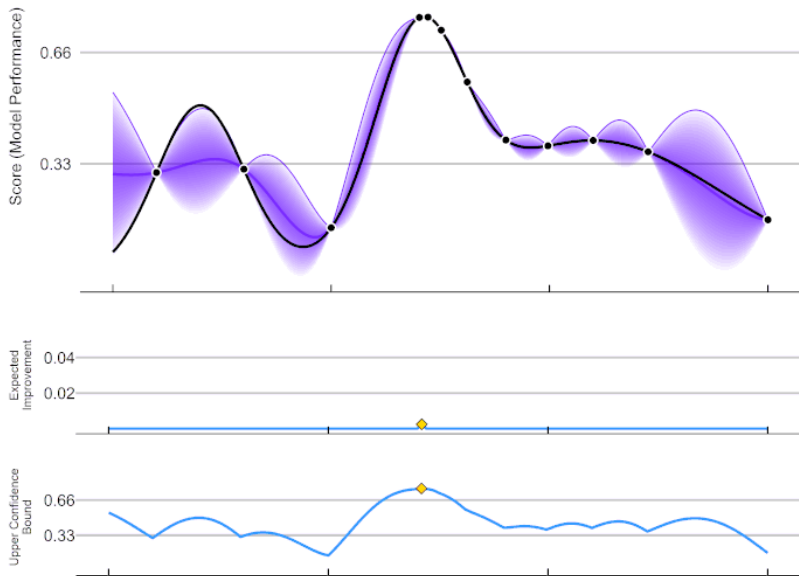
Exploration/Exploitation



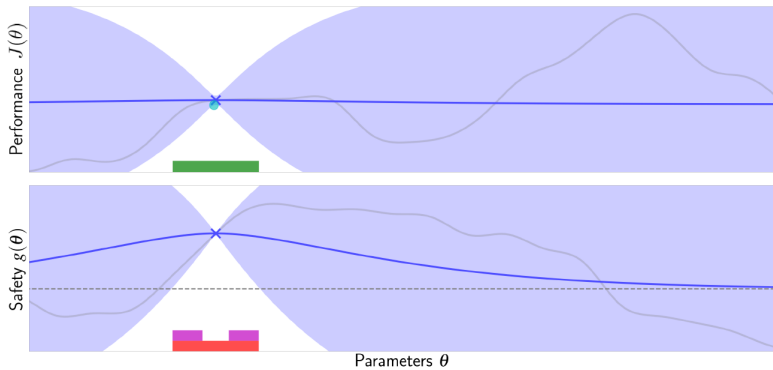
Exploration/Exploitation



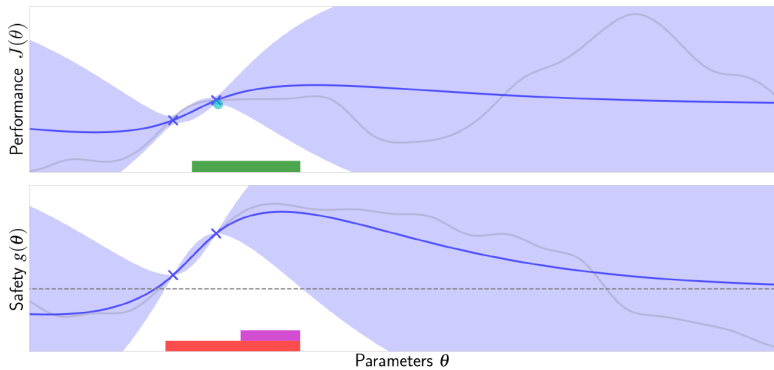
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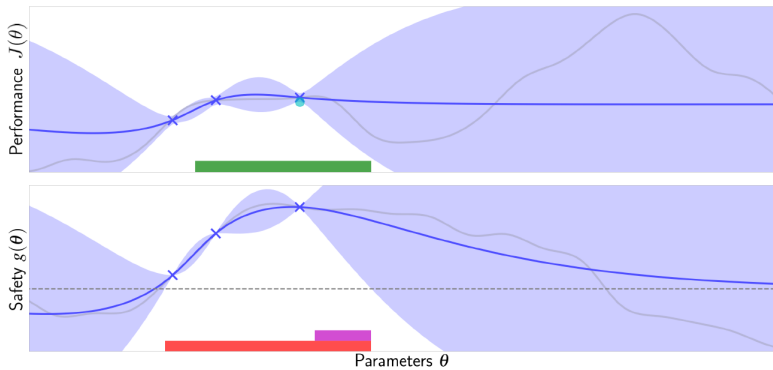
Safe Explore/Exploit



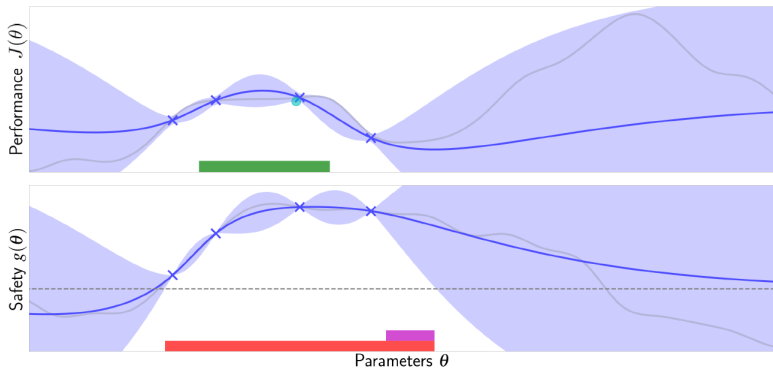
Safe Explore/Exploit



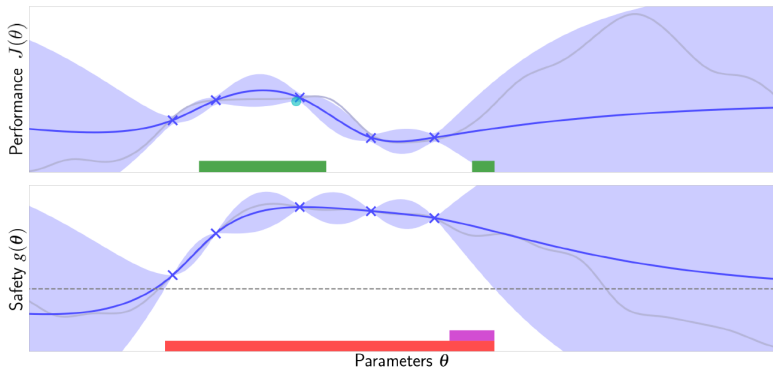
Safe Explore/Exploit



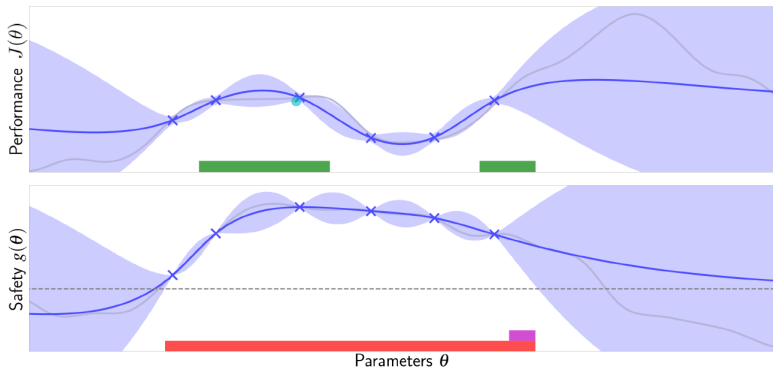
Safe Explore/Exploit



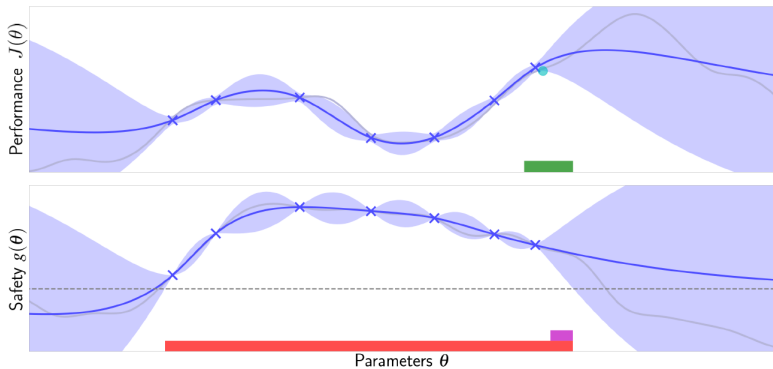
Safe Explore/Exploit



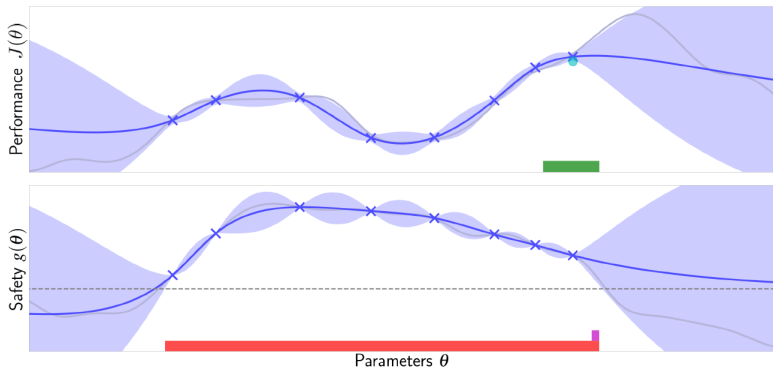
Safe Explore/Exploit



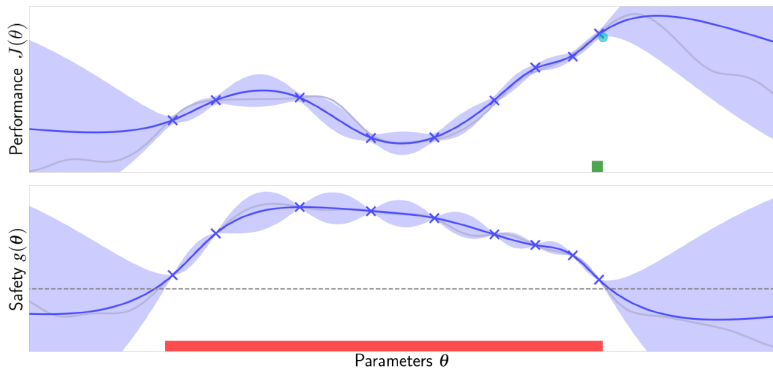
Safe Explore/Exploit



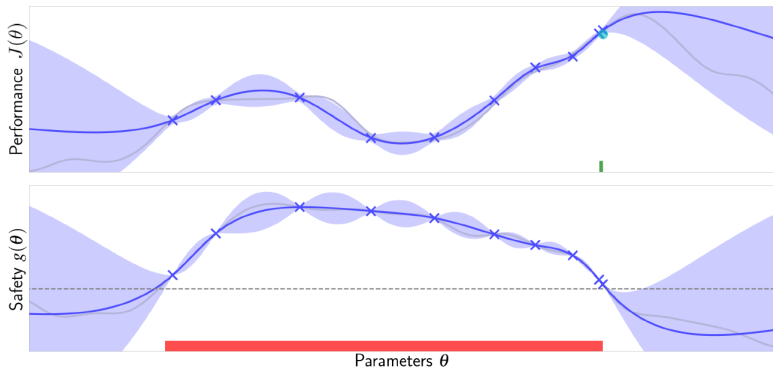
Safe Explore/Exploit



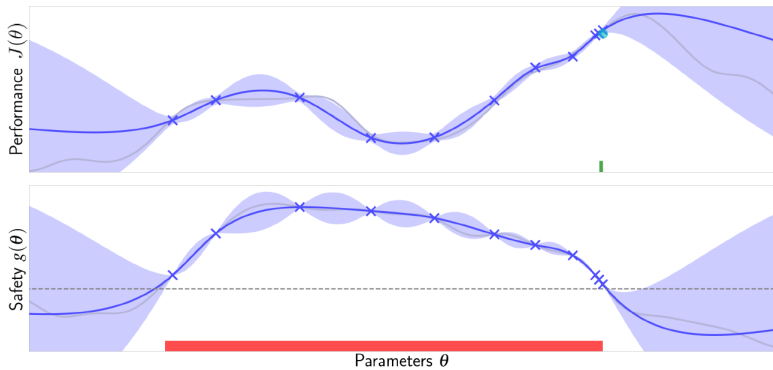
Safe Explore/Exploit



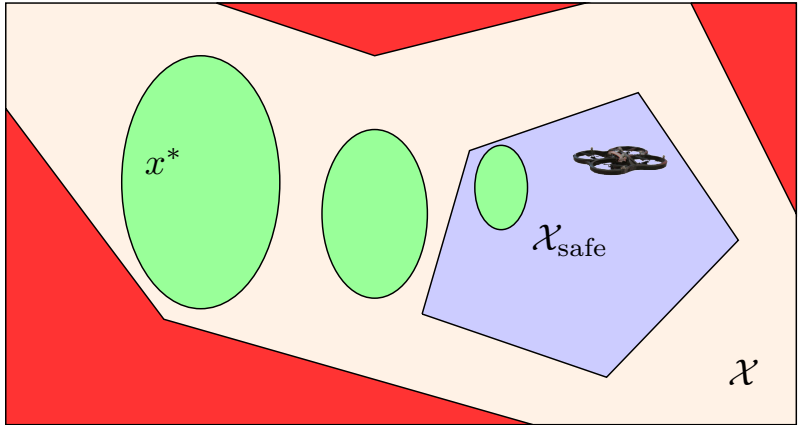
Safe Explore/Exploit



Safe Explore/Exploit



Ideal result



Slight issue: propagating uncertainty

$g(x)$ might be linear/convex but $g(\theta)$ is not

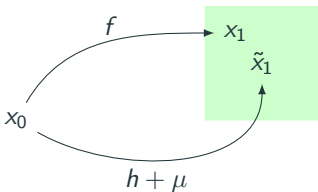
Slight issue: propagating uncertainty

$g(x)$ might be linear/convex but $g(\theta)$ is not

$$g(f(x, u = \text{Model}(x, \theta)))$$

Slight issue: propagating uncertainty

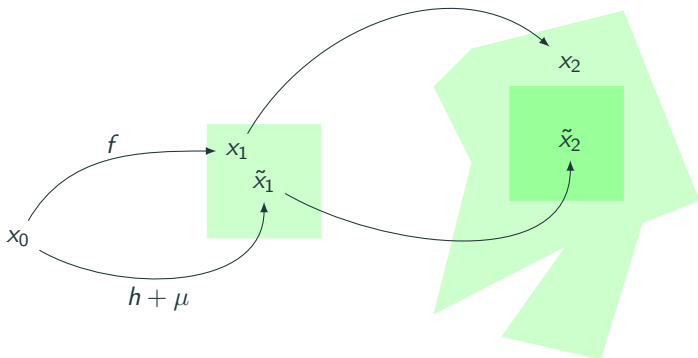
$g(x)$ might be linear/convex but $g(\theta)$ is not



$$|\mu(x, u) - e(x, u)| \leq \beta\sigma(x, u)$$

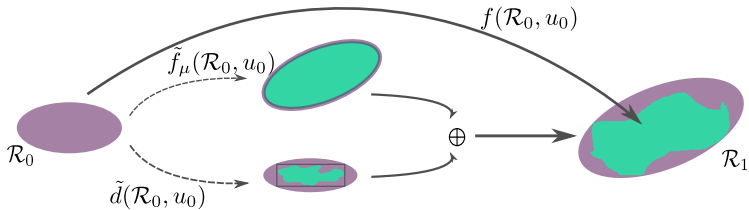
Slight issue: propagating uncertainty

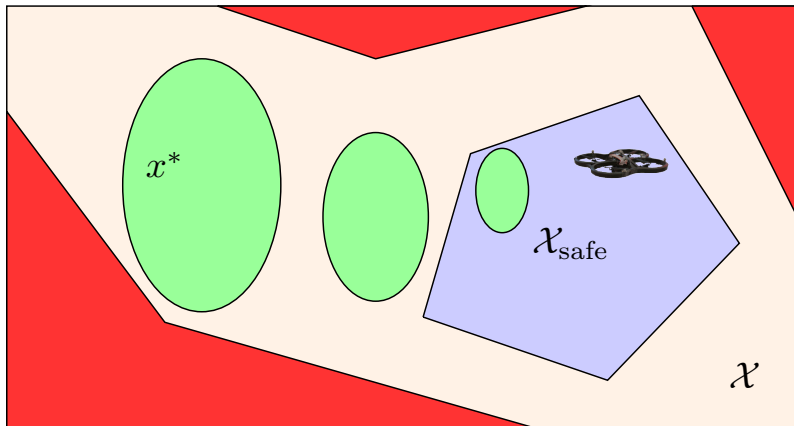
$g(x)$ might be linear/convex but $g(\theta)$ is not

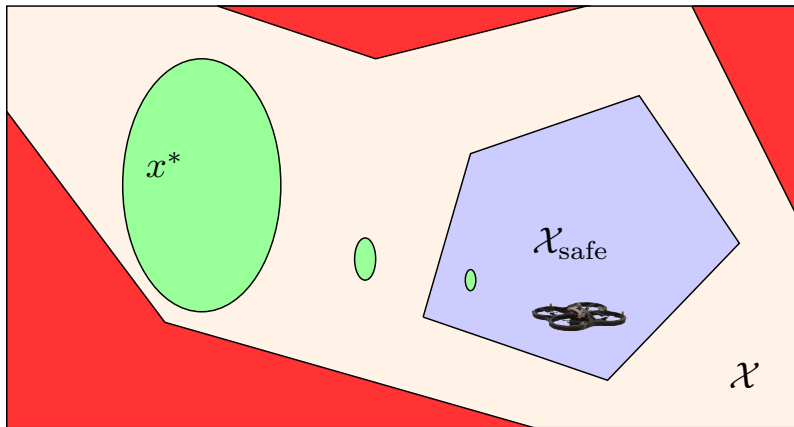


$$|\mu(x, u) - e(x, u)| \leq \beta\sigma(x, u)$$

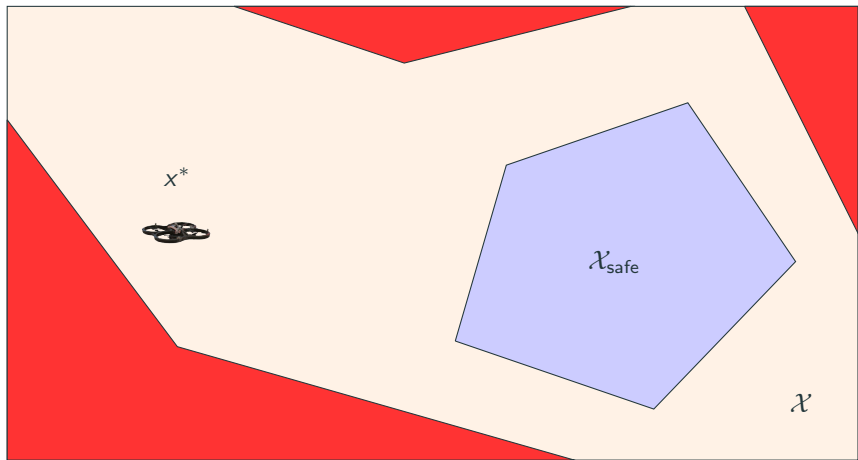
Linearized uncertainty propagation



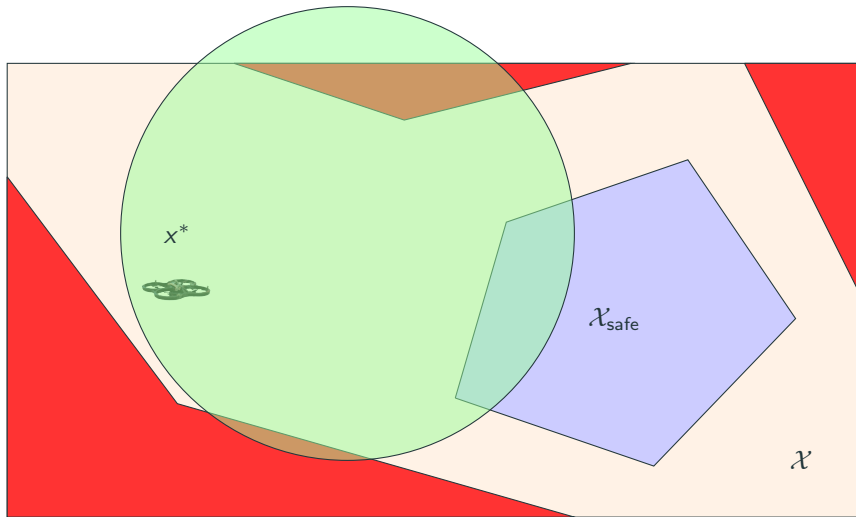




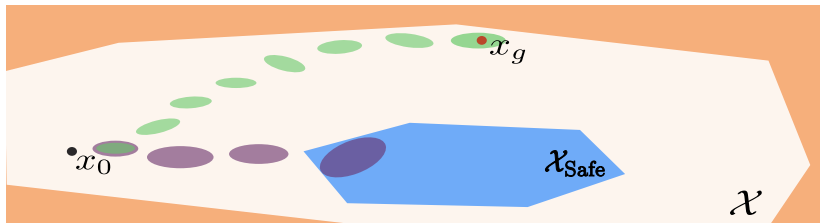
One last thing...



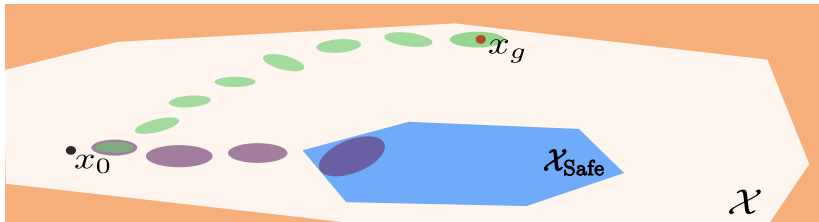
One last thing...



Simultaneous planning



Simultaneous planning



- A safe default controller
- A definition of the boundaries
- A well specified Gaussian Process
- The Lipschitz constant of the model error
- Bayesian Optimization Model Predictive Control