

Finding Errors of Hybrid Systems by Optimising an Abstraction-Based Quality Estimate

Stefan Ratschan Jan-Georg Smaus

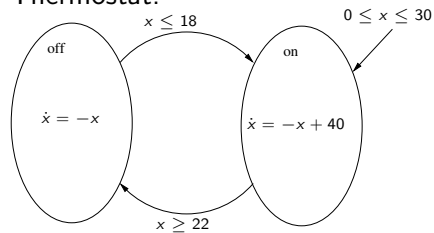
Institute of Computer Science of the Czech Academy of Sciences

Albert-Ludwigs-Universität Freiburg

July 3, 2009

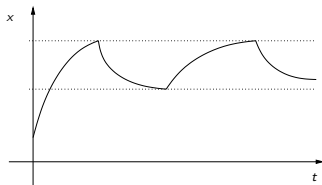
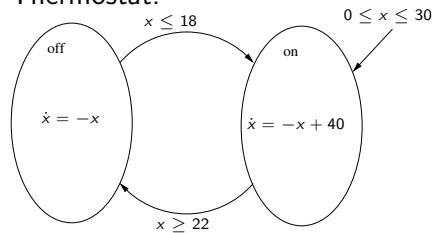
Hybrid Systems

Thermostat:



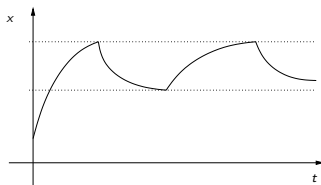
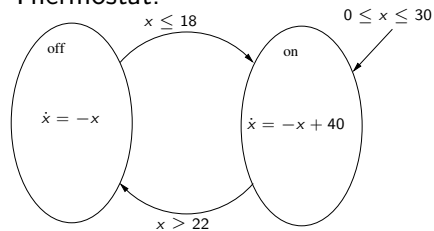
Hybrid Systems

Thermostat:



Hybrid Systems

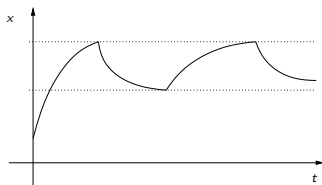
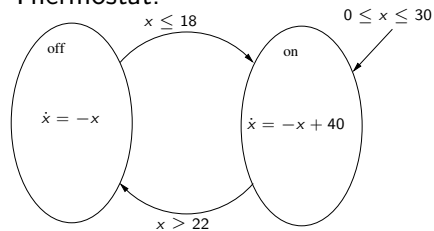
Thermostat:



Dynamical system with **both continuous** and **discrete** state and evolution.

Hybrid Systems

Thermostat:

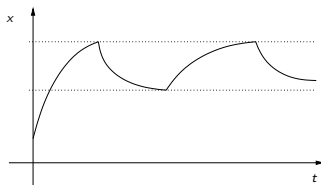
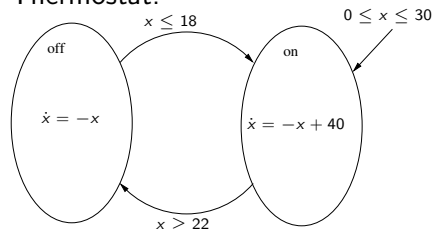


Dynamical system with **both continuous** and **discrete** state and evolution.

Also continuous state can **jump** discontinuously (state updates)

Hybrid Systems

Thermostat:



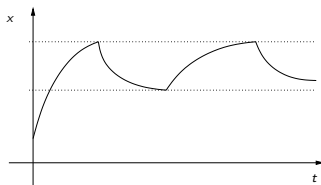
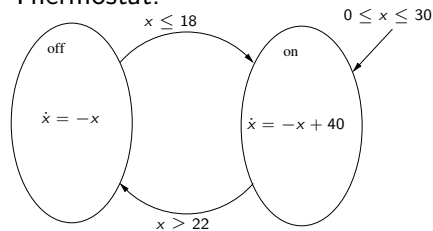
Dynamical system with **both continuous** and **discrete** state and evolution.

Also continuous state can **jump** discontinuously (state updates)

Non-linearity (differential equations, updates)

Hybrid Systems

Thermostat:



Dynamical system with **both continuous** and **discrete** state and evolution.

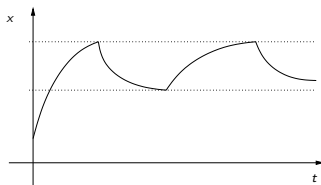
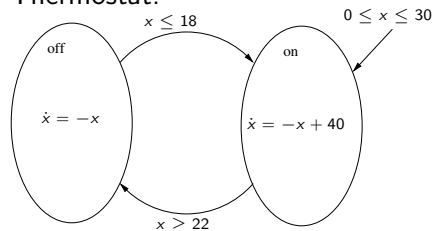
Also continuous state can **jump** discontinuously (state updates)

Non-linearity (differential equations, updates)

In illustrations: systems with just **one** control mode.

Hybrid Systems

Thermostat:



Dynamical system with **both continuous** and **discrete** state and evolution.

Also continuous state can **jump** discontinuously (state updates)

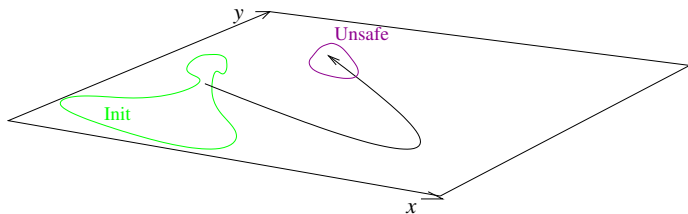
Non-linearity (differential equations, updates)

In illustrations: systems with just **one** control mode.

Motivation: embedded systems, motor gears, ...

System Correctness

Error trajectory: trajectory from initial to unsafe state



System is *correct (safe)* if it does **not** contain an **error** trajectory

Problem Definition

Observation:

- ▶ for ordinary differential equations **forward reachability computation** (as used in most verification algorithms) only with **over-approximation**.
- ▶ So: from this, no (systematic) detection **of error trajectories**

Problem Definition

Observation:

- ▶ for ordinary differential equations **forward reachability computation** (as used in most verification algorithms) only with **over-approximation**.
- ▶ So: from this, no (systematic) detection **of error trajectories**

So: design algorithm to **detect incorrectness** (*falsification* algorithm)

Illustration of the Problem

Illustration of the Problem

Assumptions:

- ▶ **deterministic** evolution: for a given initial state, unique trajectory

Illustration of the Problem

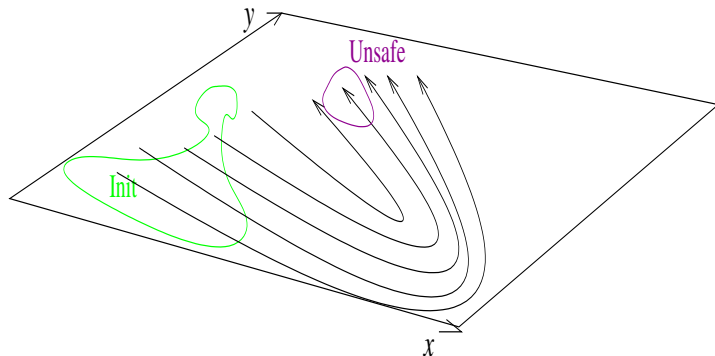
Assumptions:

- ▶ **deterministic** evolution: for a given initial state, unique trajectory
- ▶ **bounded** state space

Illustration of the Problem

Assumptions:

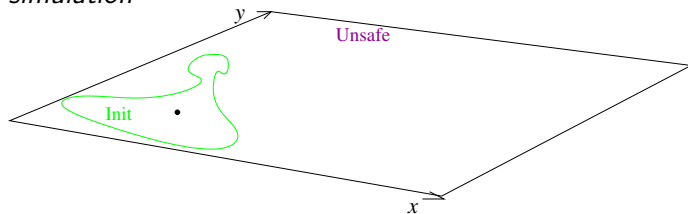
- ▶ **deterministic** evolution: for a given initial state, unique trajectory
- ▶ **bounded** state space



So, problem: finding a **startpoint** of an error trajectory.

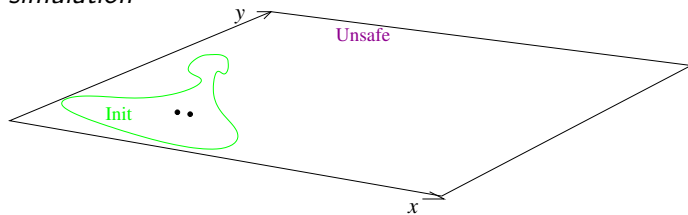
Computing trajectories

simulation



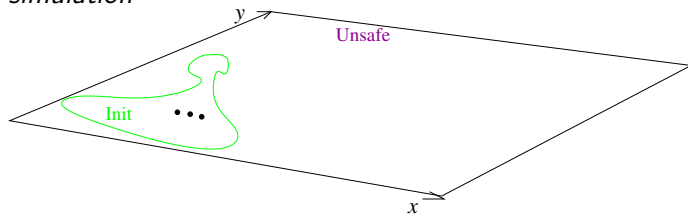
Computing trajectories

simulation



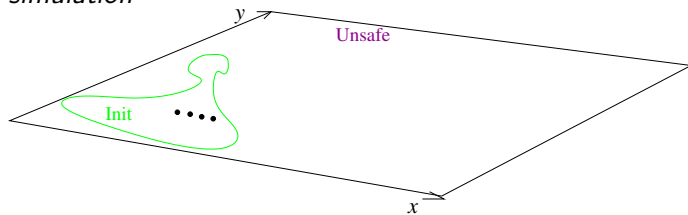
Computing trajectories

simulation



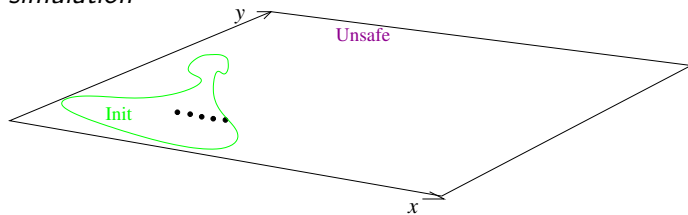
Computing trajectories

simulation



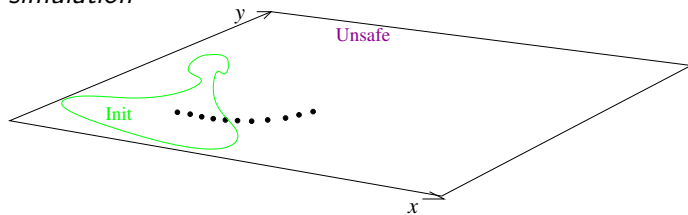
Computing trajectories

simulation



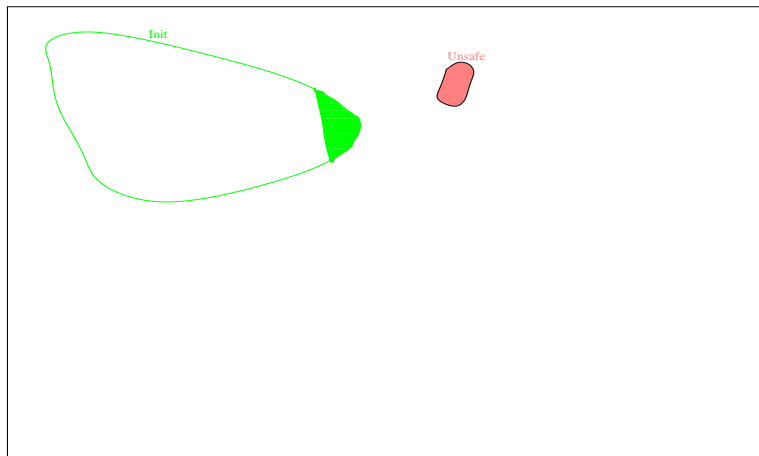
Computing trajectories

simulation



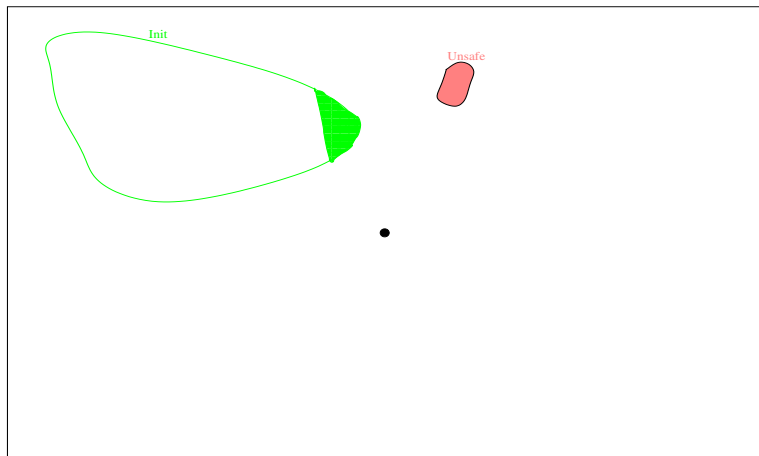
Naïve Method

starting points of simulations



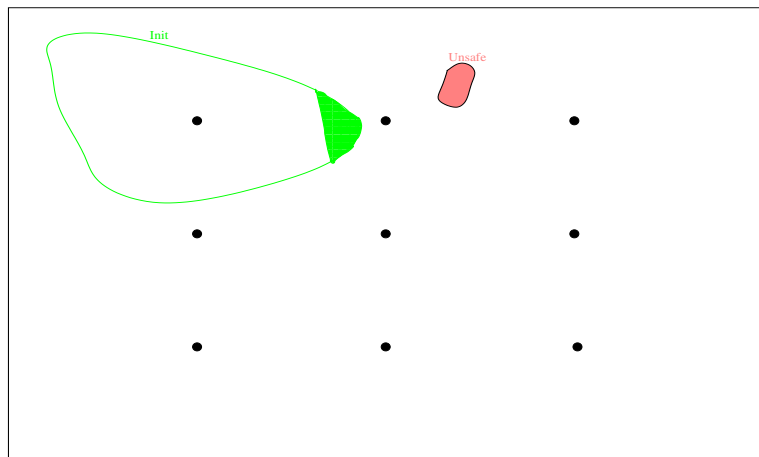
Naïve Method

starting points of simulations



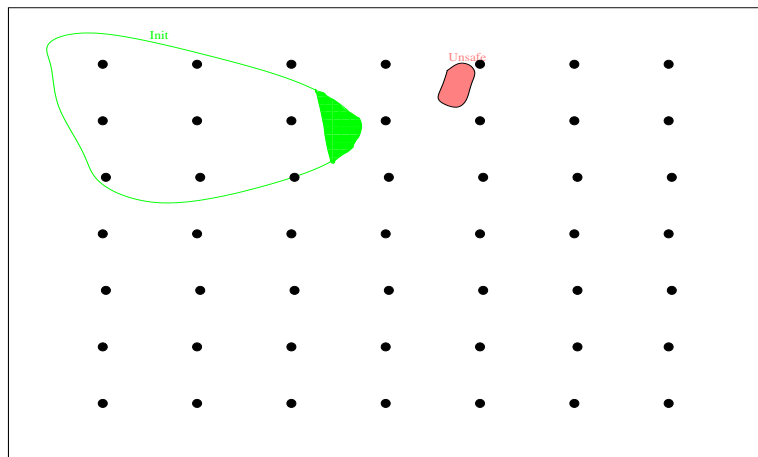
Naïve Method

starting points of simulations



Naïve Method

starting points of simulations



What to Do about the Naïve Method?

Naïve because:

- ▶ It **runs forever** on safe systems.
- ▶ It runs simulations **evenly distributed** on the whole statespace.
- ▶ Each individual simulation runs for a **pre-determined** amount of **time**.

What to Do about the Naïve Method?

Naïve because:

- ▶ It **runs forever** on safe systems.
- ▶ It runs simulations **evenly distributed** on the whole statespace.
- ▶ Each individual simulation runs for a **pre-determined** amount of **time**.

Therefore we will ...

- ▶ ... alternate **verification** and **falsification** cycles;
- ▶ ... **prefer** the more **promising** simulations;
- ▶ ... **cancel** simulations when they do **not** look **promising** anymore.

HSOLVER Abstraction

Verification tool: HSOLVER

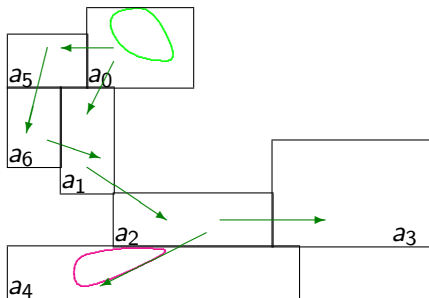
(<http://hsolver.sourceforge.net/>)

HSOLVER Abstraction

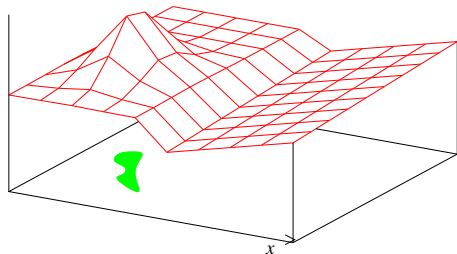
Verification tool: HSOLVER

(<http://hsolver.sourceforge.net/>)

- ▶ The statespace is partitioned into finitely many **boxes**.
- ▶ Interval arithmetic is used to compute the **abstract transitions**.
- ▶ Overapproximation used for **verification**.
- ▶ If necessary, the abstraction is refined by **splitting** a box.
- ▶ State space **pruning**



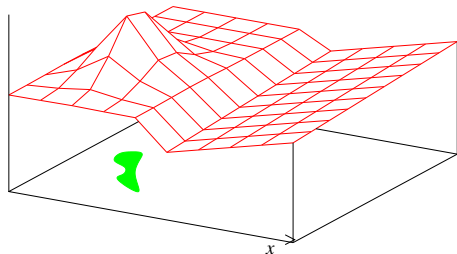
Our Method: Main Idea



Use real-valued *quality estimate* to approximate "given point is close to an initial point of an error trajectory".

Optimise the *quality estimate*.

Our Method: Main Idea



Use real-valued *quality estimate* to approximate "given point is close to an initial point of an error trajectory".

Optimise the *quality estimate*.

- ▶ How to define this function?
- ▶ How to find the optimum?

Defining the Quality Estimate

Overall approach:

- ▶ Start a **simulation**
- ▶ Compute closeness to error trajectory **on the fly**
- ▶ **Cancel** if **no new information** gained

Defining the Quality Estimate

Overall approach:

- ▶ Start a **simulation**
- ▶ Compute closeness to error trajectory **on the fly**
- ▶ **Cancel** if **no new information** gained

Problems: a-priori, **length** of error trajectories **unbounded**, and

- ▶ the **longer** we simulate, the more information about quality, but simulation **costs**
- ▶ a simulation that looks **bad** at the **beginning**, might turn out **good** much **later**

Defining the Quality Estimate

Overall approach:

- ▶ Start a **simulation**
- ▶ Compute closeness to error trajectory **on the fly**
- ▶ **Cancel** if **no new information** gained

Problems: a-priori, **length** of error trajectories **unbounded**, and

- ▶ the **longer** we simulate, the more information about quality, but simulation **costs**
- ▶ a simulation that looks **bad** at the **beginning**, might turn out **good** much **later**

Solution: Use information from **abstraction**, s.t. fine enough abstraction will result in reliable quality estimate

Closeness to Error Trajectory

A simulation is **close** to an **error** trajectory iff

- ▶ its first point is **initial**

Closeness to Error Trajectory

A simulation is **close** to an **error** trajectory iff

- ▶ its first point is **initial**
- ▶ it stays **inside of abstraction** as much as possible

Closeness to Error Trajectory

A simulation is **close** to an **error** trajectory iff

- ▶ its first point is **initial**
- ▶ it stays **inside of abstraction** as much as possible
- ▶ it gets **close to unsafe** state

Closeness to Error Trajectory

A simulation is **close** to an **error** trajectory iff

- ▶ its first point is **initial**
- ▶ it stays **inside of abstraction** as much as possible
- ▶ it gets **close to unsafe** state

Note: leaving abstraction means "no error trajectory"

Closeness to Error Trajectory

A simulation is **close** to an **error** trajectory iff

- ▶ its first point is **initial**
- ▶ it stays **inside of abstraction** as much as possible
- ▶ it gets **close to unsafe** state

Note: leaving abstraction means "no error trajectory"

But: there might still be an error trajectory **nearby**

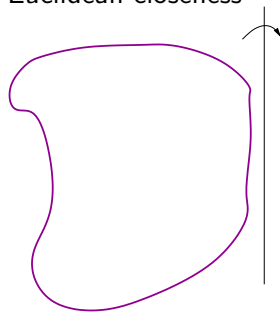
Closeness to Unsafe State

Maximal closeness of any **individual simulation point**

Closeness to Unsafe State

Maximal closeness of any **individual simulation point**

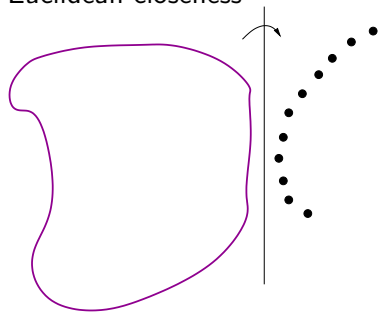
This is **not**
Euclidean closeness



Closeness to Unsafe State

Maximal closeness of any **individual simulation point**

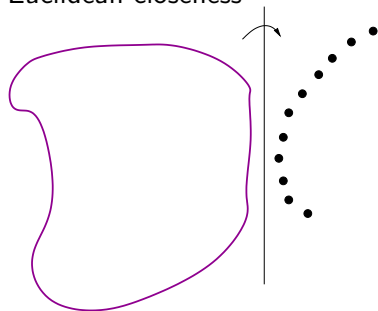
This is **not**
Euclidean closeness



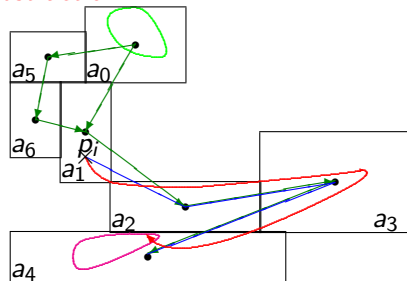
Closeness to Unsafe State

Maximal closeness of any **individual simulation point**

This is **not**
Euclidean closeness



Measure closeness using
abstraction



Cancellation Strategy

Goal: **Cancel** if **no** interesting **new information** gained

Cancellation Strategy

Goal: **Cancel** if **no** interesting **new information** gained

Problem: based on future (when new information might be gained)

Cancellation Strategy

Goal: **Cancel** if **no** interesting **new information** gained

Problem: based on future (when new information might be gained)

Cancel if

- ▶ **unsafe** state hit,
- ▶ **outside** of **abstraction** for too long, or
- ▶ **no improvement** of quality for too long.

"too long": parameter *sim_cnc*

Cancellation Strategy

Goal: **Cancel** if **no** interesting **new information** gained

Problem: based on future (when new information might be gained)

Cancel if

- ▶ **unsafe** state hit,
- ▶ **outside** of **abstraction** for too long, or
- ▶ **no improvement** of quality for too long.

"too long": parameter *sim_cnc*

Observation: last two items **improve with abstraction**

Cancellation Strategy

Goal: **Cancel** if **no** interesting **new information** gained

Problem: based on future (when new information might be gained)

Cancel if

- ▶ **unsafe** state hit,
- ▶ **outside** of **abstraction** for too long, or
- ▶ **no improvement** of quality for too long.

"too long": parameter *sim_cnc*

Observation: last two items **improve with abstraction**

Hope: abstraction **eventually good enough** for reliable strategy

Optimising the Quality Estimate

From boxes that might contain initial states,
start **numerical local optimisation**.

Optimising the Quality Estimate

From boxes that might contain initial states,
start **numerical local optimisation**.

Numerical optimisation usually needs **derivatives**.

Optimising the Quality Estimate

From boxes that might contain initial states,
start **numerical local optimisation**.

Numerical optimisation usually needs **derivatives**.

Not available! *direct search* methods

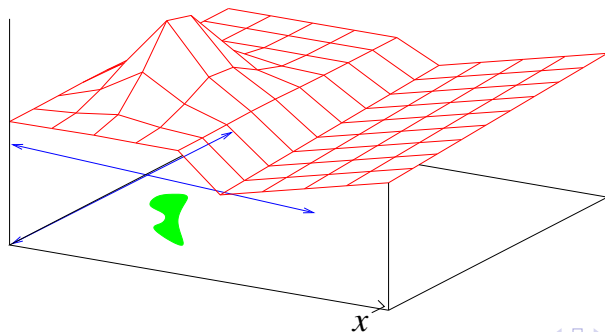
Optimising the Quality Estimate

From boxes that might contain initial states,
start **numerical local optimisation**.

Numerical optimisation usually needs **derivatives**.

Not available! *direct search* methods

Compass method



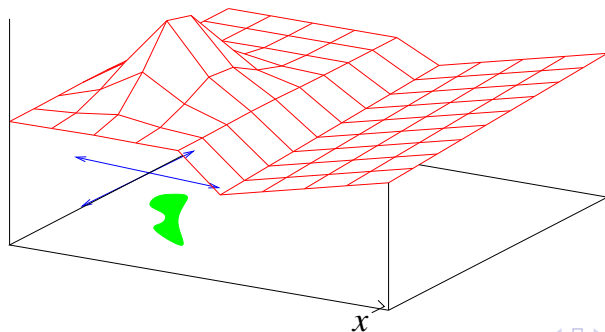
Optimising the Quality Estimate

From boxes that might contain initial states, start **numerical local optimisation**.

Numerical optimisation usually needs **derivatives**.

Not available! *direct search* methods

Compass method



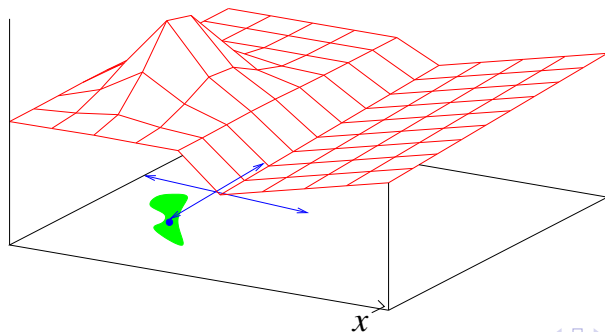
Optimising the Quality Estimate

From boxes that might contain initial states,
start **numerical local optimisation**.

Numerical optimisation usually needs **derivatives**.

Not available! *direct search* methods

Compass method



Experiments

	our algorithm				naïve algorithm	
Example	<i>sim_cnc</i>	time	ref.	sim.	time	sim.
convoi	200	0.04	0	1	∞	∞
eco	400	0.1	0	1	0.1	1
eco	200	2.1	10	63	0.1	1
focus	200	0.1	0	10	0.04	1
focus	20	29.7	434	288	0.04	1
parabola	105	0.0	0	1	∞	∞
parabola	30	18.0	353	113	∞	∞

Jumps

- ▶ For simplicity, we did not explain here how the **quality estimate** is defined in the presence of **jumps**.
- ▶ Our current implementation **did** find error trajectories with up to **2** (necessary) jumps.
- ▶ Encouraging first result, but topic for **future work**.

Conclusion

Main Observations:

- ▶ **Local search** can help to find error trajectories.
- ▶ Even for too small value of *sim_cnc*, simulations will eventually “survive” long enough thanks to the **refinement** of the abstraction and **improving faithfulness** of the quality function.

Conclusion

Main Observations:

- ▶ **Local search** can help to find error trajectories.
- ▶ Even for too small value of *sim_cnc*, simulations will eventually “survive” long enough thanks to the **refinement** of the abstraction and **improving faithfulness** of the quality function.

Future work:

- ▶ More **mathematical** intelligence (e.g., derivatives)
- ▶ Reasoning forward **and backward**
- ▶ **Non-deterministic** evolution