

# Génération de trajectoires avec contraintes temporelles

a.k.a. SCvx-STL

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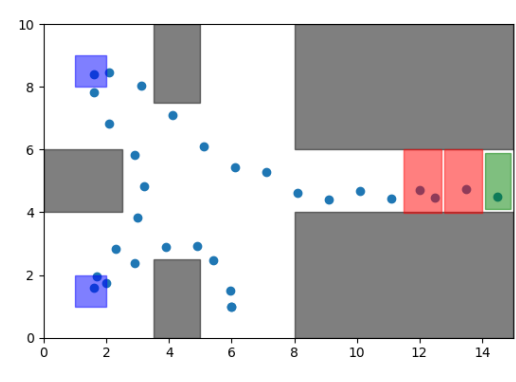
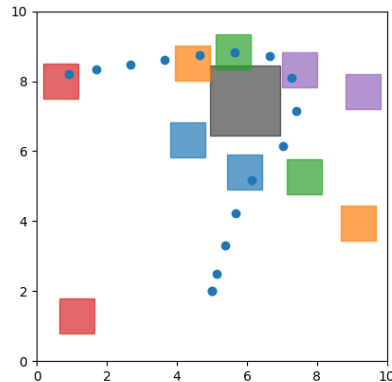
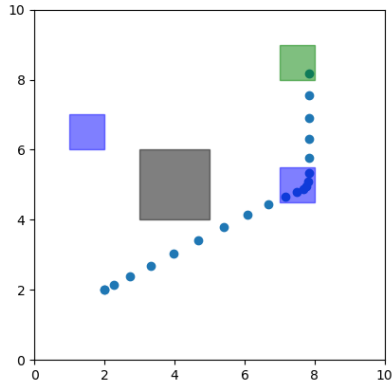
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# Motion planning with mission-based feature

Examples of behaviors of robots (w.r.t. dynamics) and mission planning

- two targets
- many targets
- hierarchy in targets



# Summary

## 1 Algorithmic orientation

- Convexity
- SCvx Overview
- Example

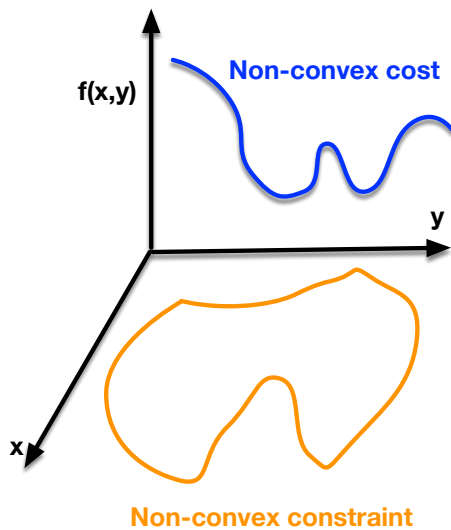
## 2 Contributions

- Python implementation
- Autocoding in C

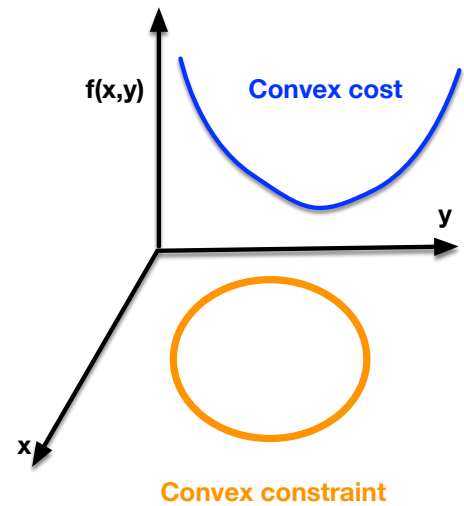
## 3 Future work

- Signal Temporal Logic

# Why convexity matters?



Convexification  
 $\Rightarrow$



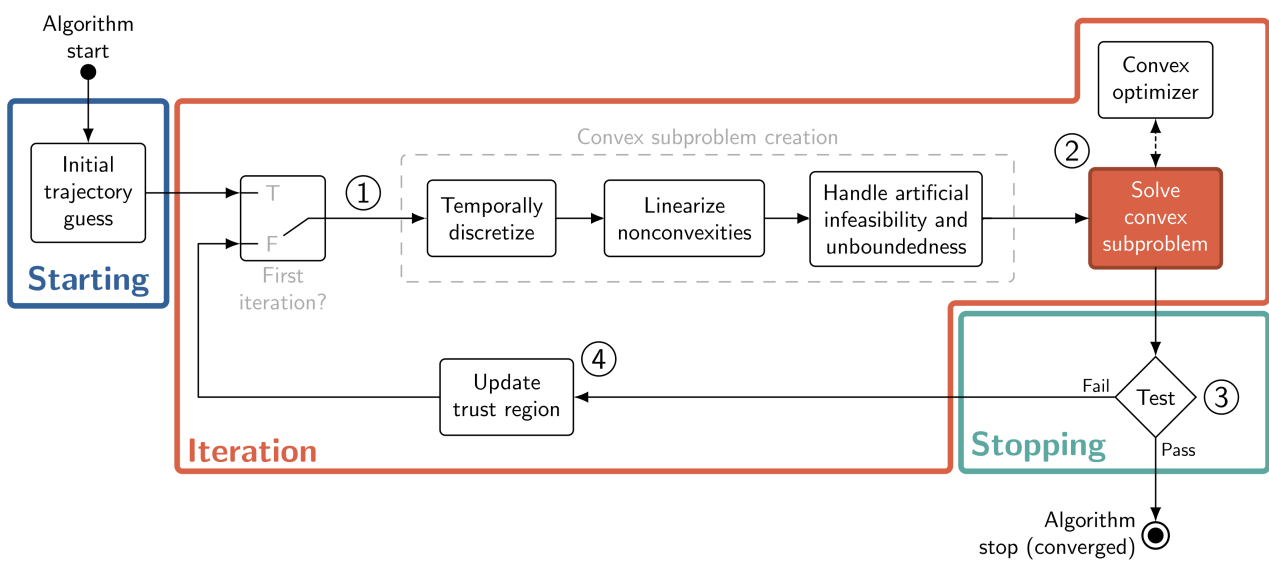
- No guarantees of convergence or complexity

Requires expert in the loop

- Guaranteed global optimum
- Polynomial-time complexity

No human in the loop needed

# SCvx Algorithm: Overview<sup>1</sup>



**Input:** Non-convex problem and number of sample points

- ① Choose an initial trajectory (e.g., straight line)
- ② Iteratively solve convex sub-problems until convergence

**Output:** a sequence of controls or a failure

<sup>1</sup>Convex Optimization for Trajectory Generation. Danylo Malyuta *et al.*, 2022

# Convexification

## Discrete-time Convex Subproblem

$$\min_{x, u, \hat{v}} \mathcal{L}(x, u, \hat{v}) \quad (1a)$$

subject to

$$x_{k+1} = A_k x_k + B_k u_k + r_k + E_k v_k, \quad \text{Linearized/discretized dynamics} \quad (1b)$$

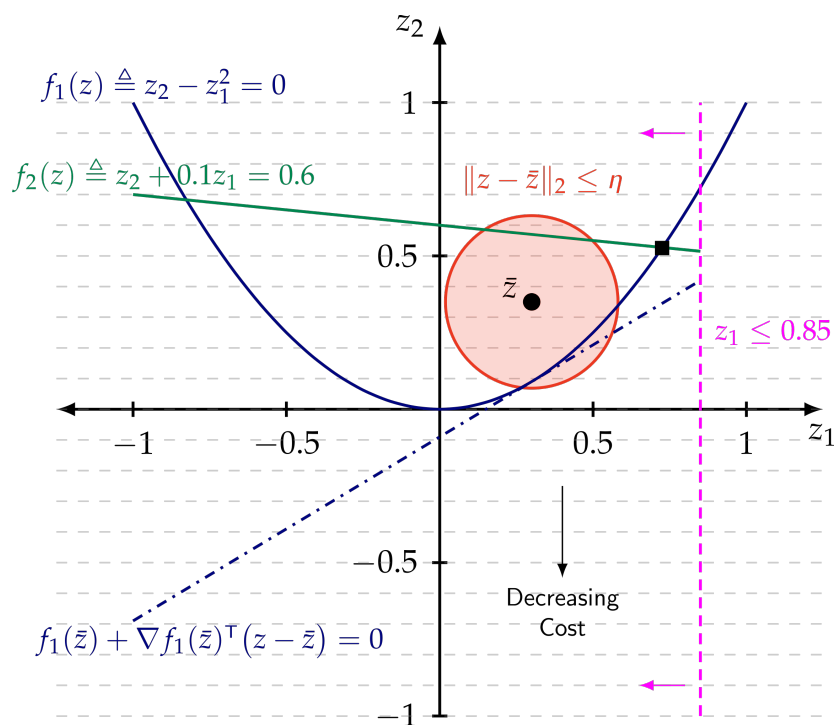
$$x_k \in \mathcal{X}_k, \quad u_k \in \mathcal{U}_k, \quad \text{State and control constraints} \quad (1c)$$

$$C_k x_k + D_k u_k + r'_k \leq v_{s,k}, \quad \text{Convexified/discretized path constraint} \quad (1d)$$

$$\|\delta x_k\|_q + \|\delta u_k\|_q \leq \eta \quad \text{Trust region} \quad (1e)$$

- $x$  is a state vector,  $u$  a control vector
- $\mathcal{X}_k$  and  $\mathcal{U}_k$  are convex sets
- $A_k, B_k, C_k, D_k, E_k$  are matrices
- $\delta$  are the difference between the subproblem solution and the linearization point

## Convex subproblem example: simple 2D cases



**Remark:** linearization can induce unbounded solution of the optimization problem. A *trust region* is inserted to keep the linearization "close to" the reference point.

# Python implementation

## Tools and Requirements

### Starting point: CVXPY

CVXPY is an open source Python-embedded modeling language for convex optimization problems<sup>a</sup>. Main ingredients:

- Based on **Disciplined Convex Programming (every constraints must be convex)**
- Based on state of the art numerical algorithms (*e.g.*, NumPy) and convex solvers (*e.g.*, ECOS)

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<sup>a</sup><https://www.cvxpy.org>

### First contribution: from CVXPY to SCVXPY

- Automatic linearization methods based on SymPy to generate symbolic gradients
- Handmade outer loop



# Dubin's car example

## Optimal problem defined by

- 2D Dubin's car dynamics

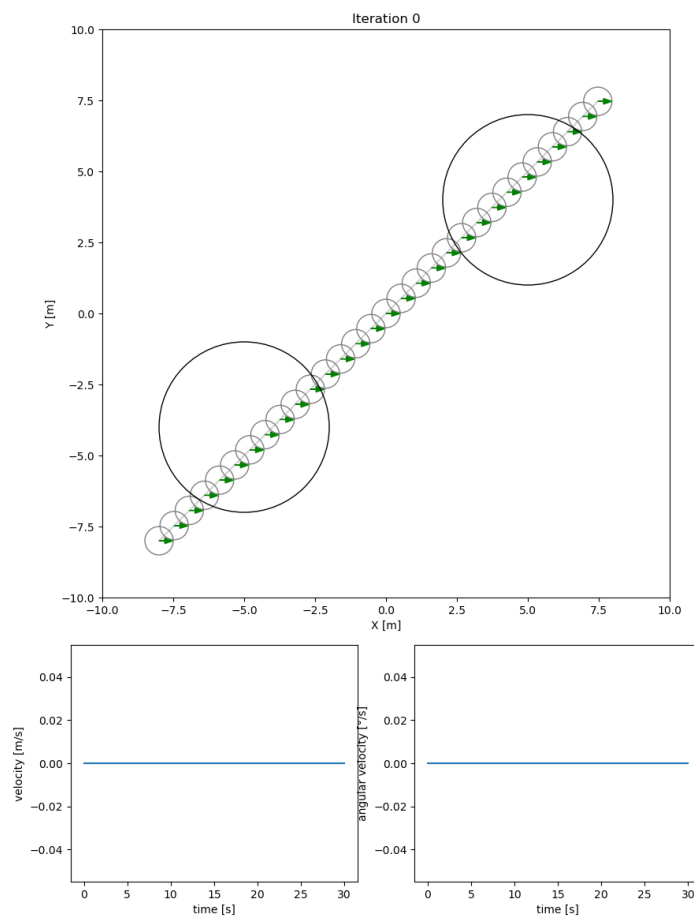
$$\dot{x} = u_1 \cos \theta, \quad \dot{y} = u_1 \sin \theta, \quad \dot{\theta} = u_2$$

- Mission: reach a target in 30 seconds and avoid obstacles

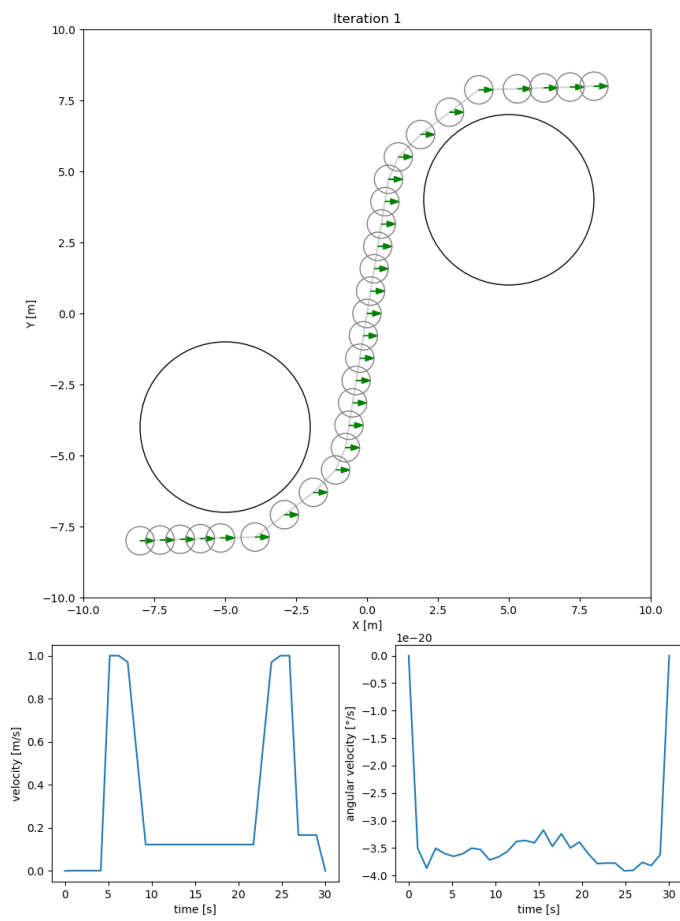
## SCVX parameters

- 30 discretization points
- Initial trust region radius sets to 5
- 10000 intermediate points for linearization

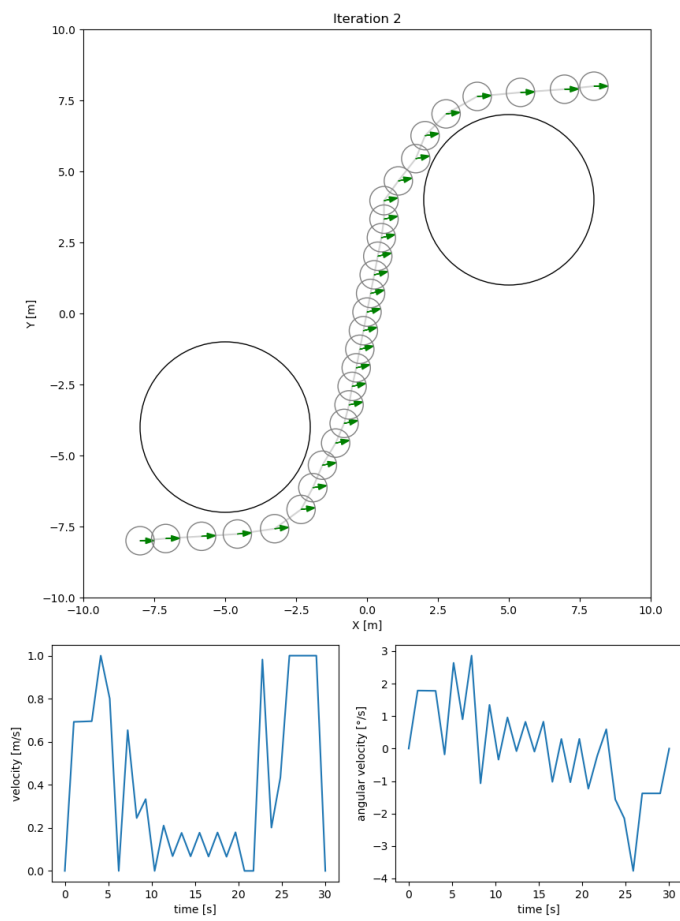
# Solution on example (Python implem.) – iteration 0



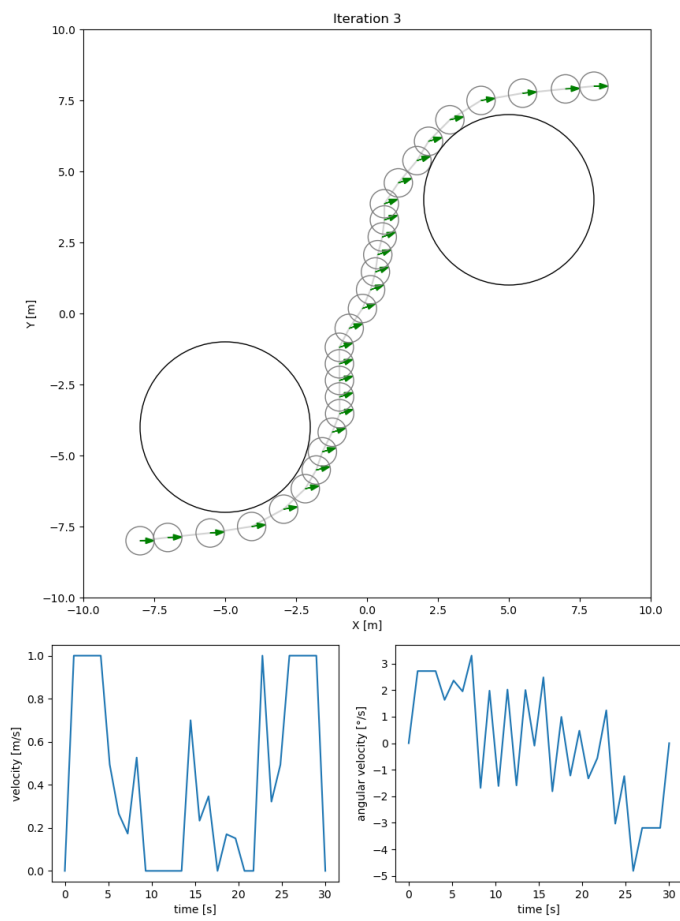
# Solution on example (Python implem.) – iteration 1



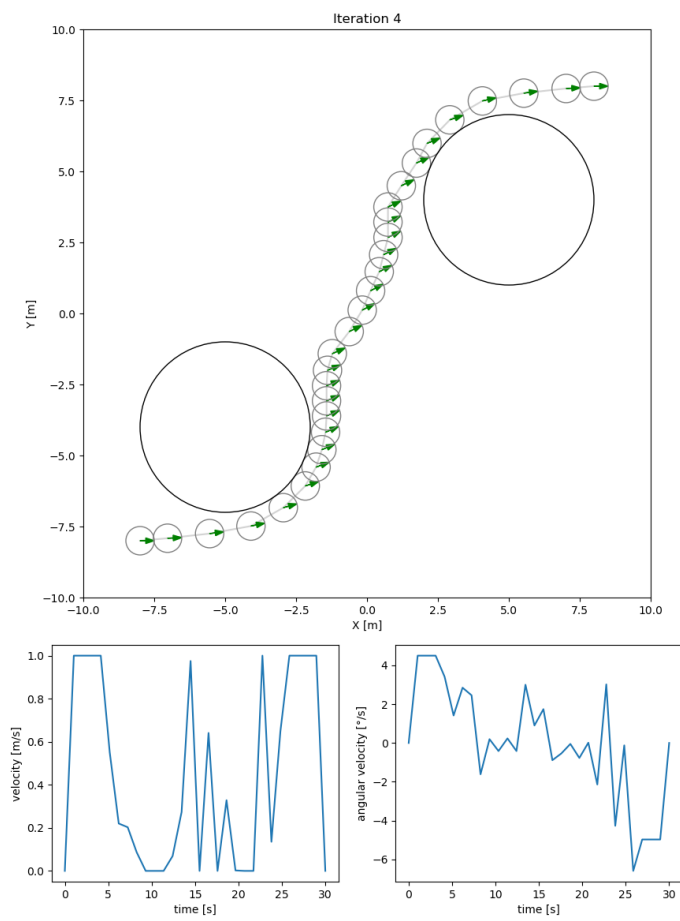
# Solution on example (Python implem.) – iteration 2



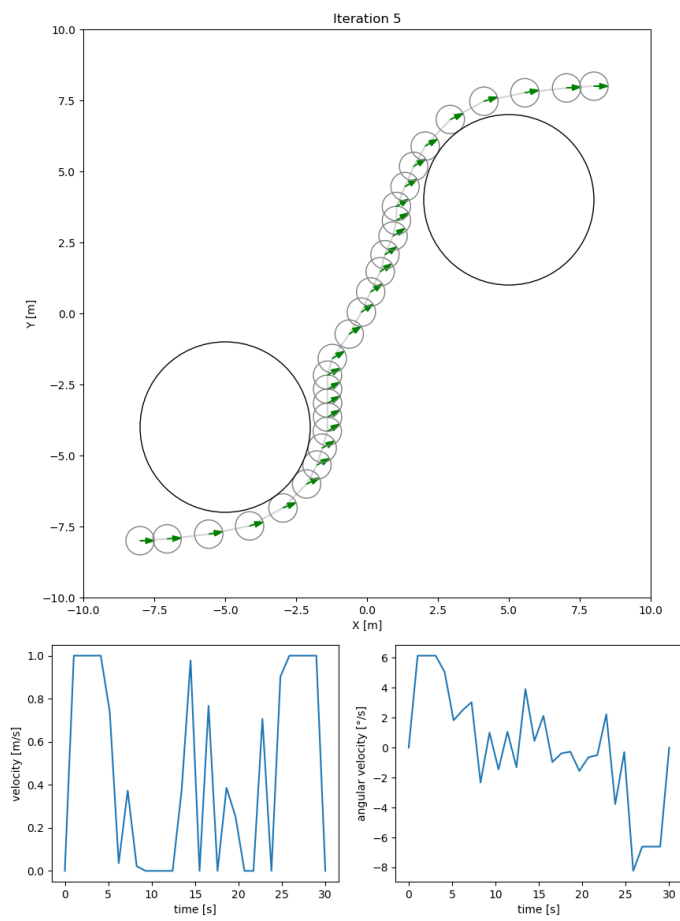
# Solution on example (Python implem.) – iteration 3



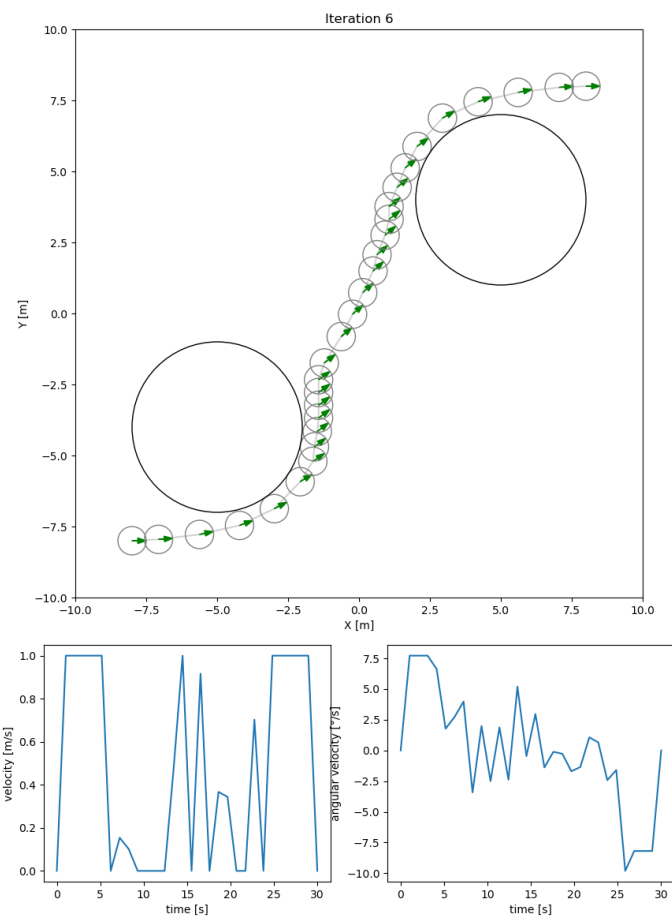
# Solution on example (Python implem.) – iteration 4



# Solution on example (Python implem.) – iteration 5

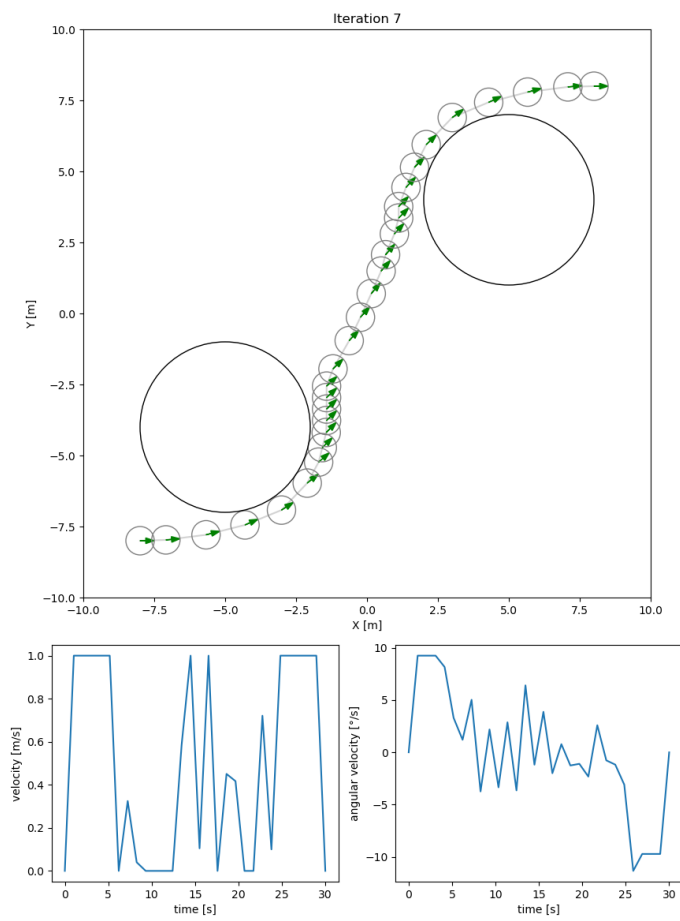


# Solution on example (Python implem.) – iteration 6

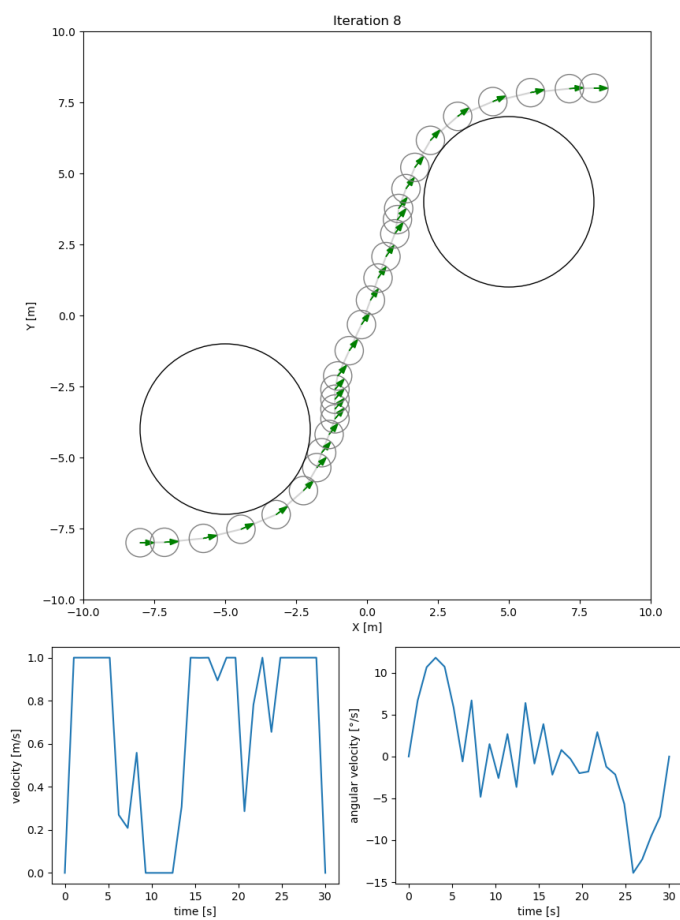




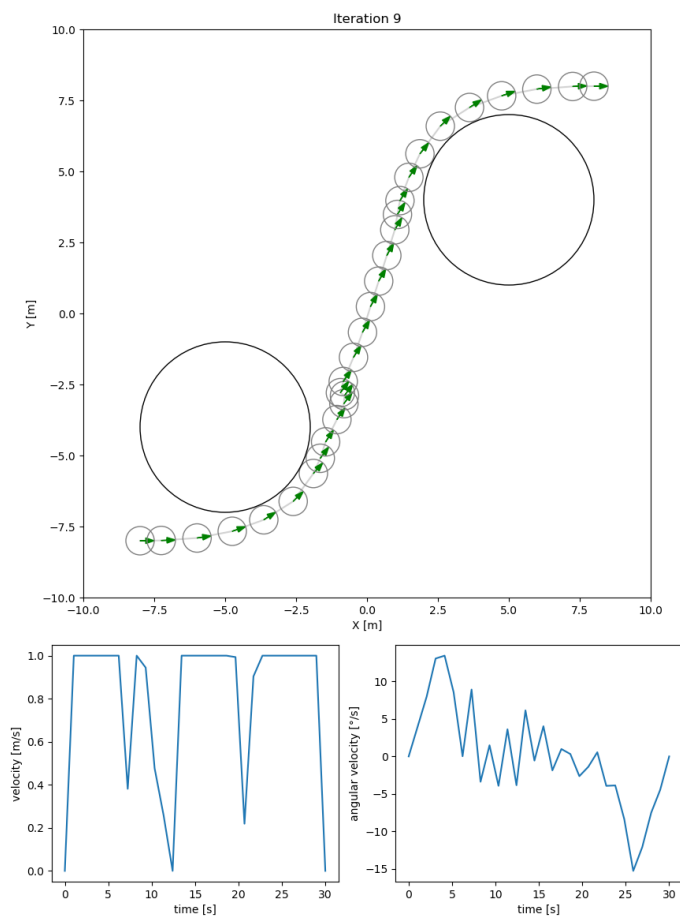
# Solution on example (Python implem.) – iteration 7



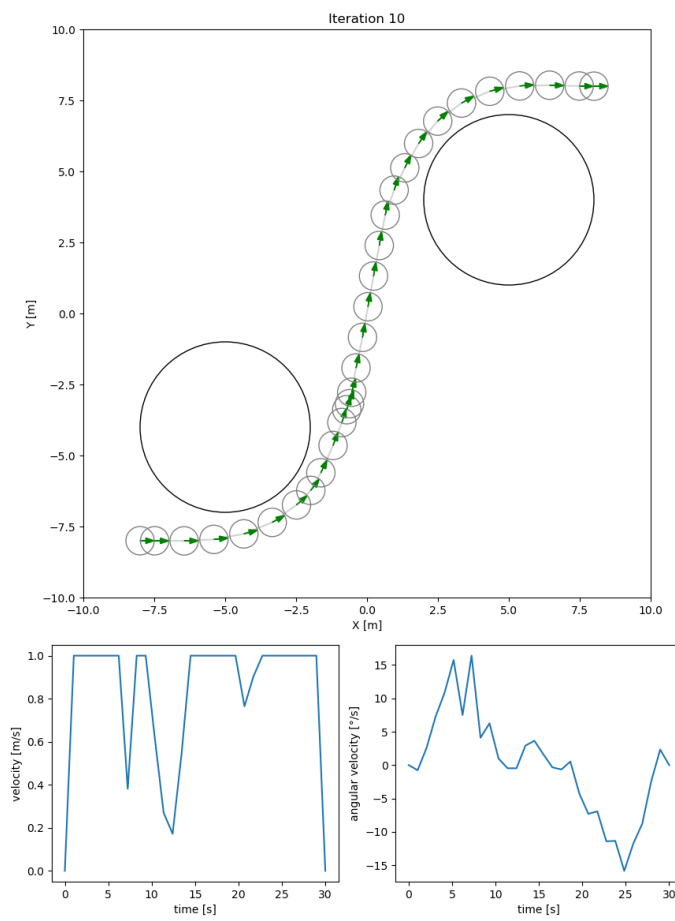
# Solution on example (Python implem.) – iteration 8



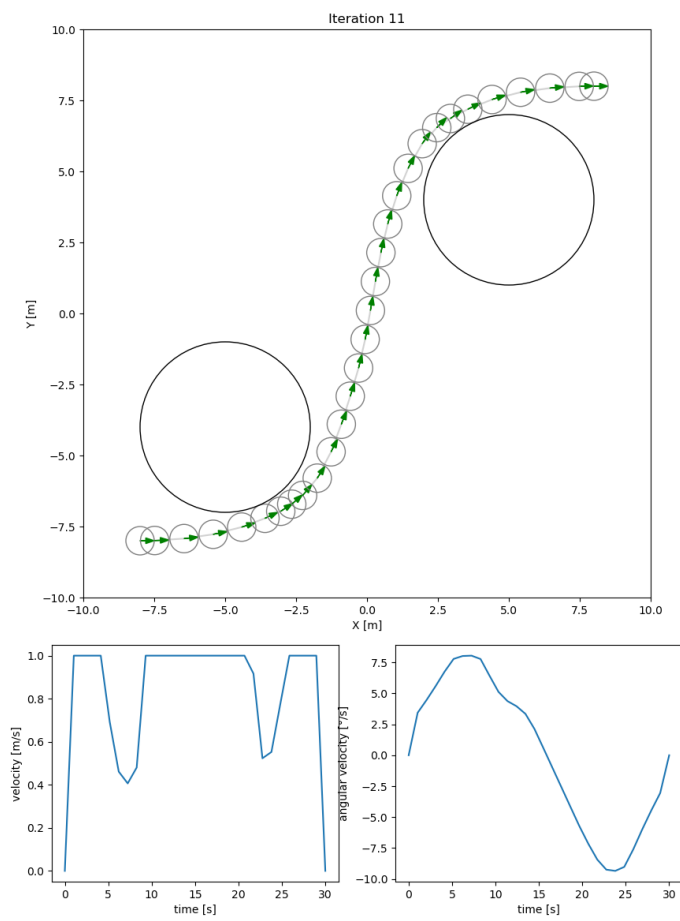
# Solution on example (Python implem.) – iteration 9



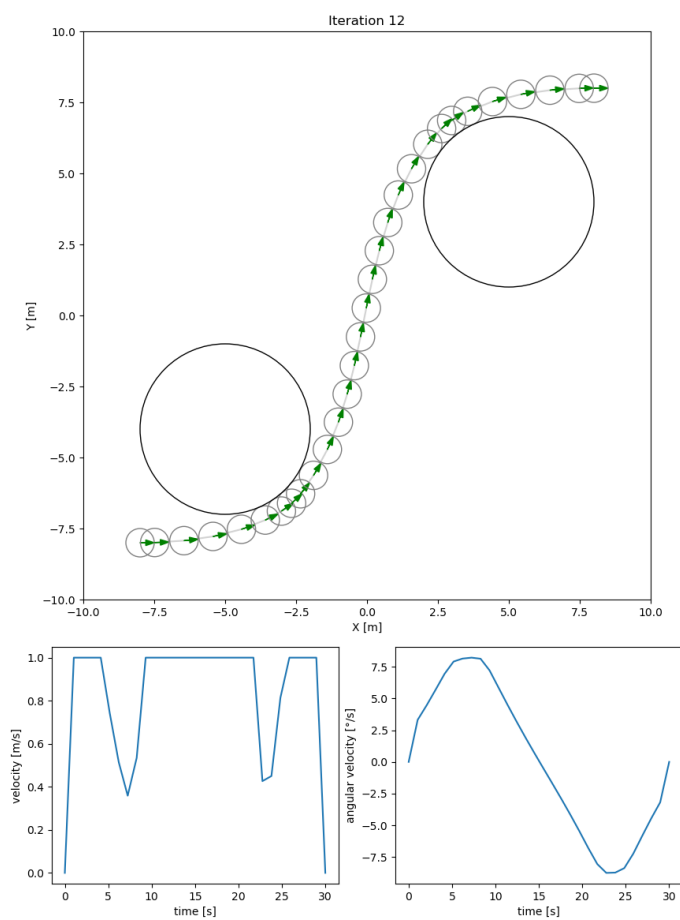
# Solution on example (Python implem.) – iteration 10



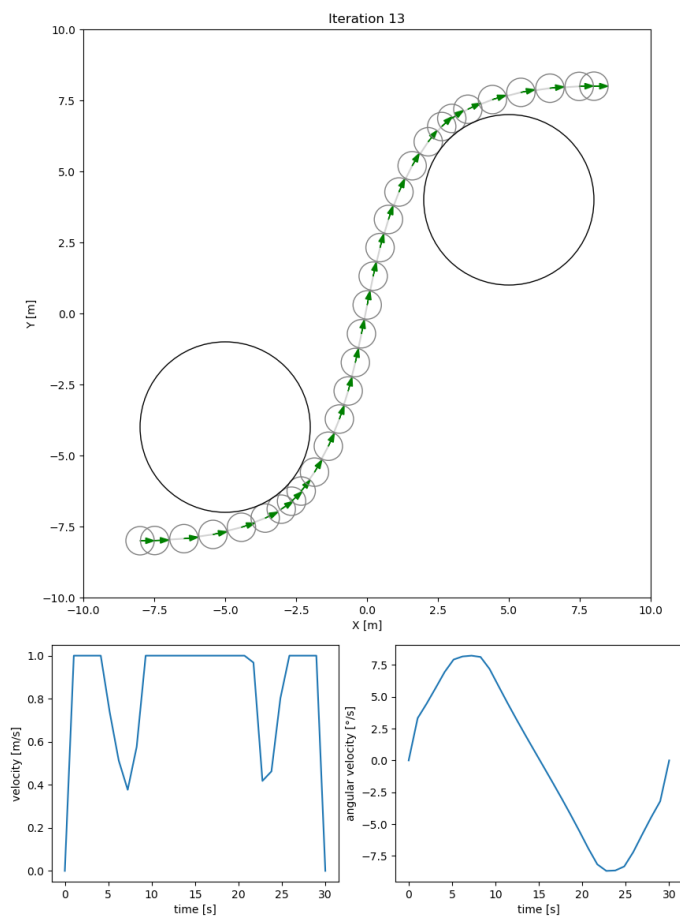
# Solution on example (Python implem.) – iteration 11



# Solution on example (Python implem.) – iteration 12



# Solution on example (Python implem.) – iteration 13



# Python code performance analysis

Command being timed: "python SCvx.py"

- User time (seconds): 3.08
- System time (seconds): 0.03
- Percent of CPU this job got: 100
- Elapsed (wall clock) time (h:mm:ss or m:ss): 0:03.12
- Maximum resident set size (kbytes): 161068



# C code generation

## Tools and Requirements

### Starting point: CVXPYGen

CVXPY is an open source Python-embedded modeling language for convex optimization problems<sup>a</sup>. Main ingredients:

- Based on **Disciplined Convex Programming** and **Disciplined Parameterized Programming**
- Based on state of the art C code generator for convex problems (*e.g.*, CVXPYgen)

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<sup>a</sup><https://www.cvxpy.org>

### Second contribution: from CVXPY to SCVXPYGen

- Automatic linearization methods based on SymPy to generate symbolic gradients and C code
- Handmade outer loop in C

# Autocoding in C

## Disciplined Parameterized Programming

DPP ensures that each constraints is composed of at most 1 parameter.  
Michael's constraint that creates a repulsive vector:

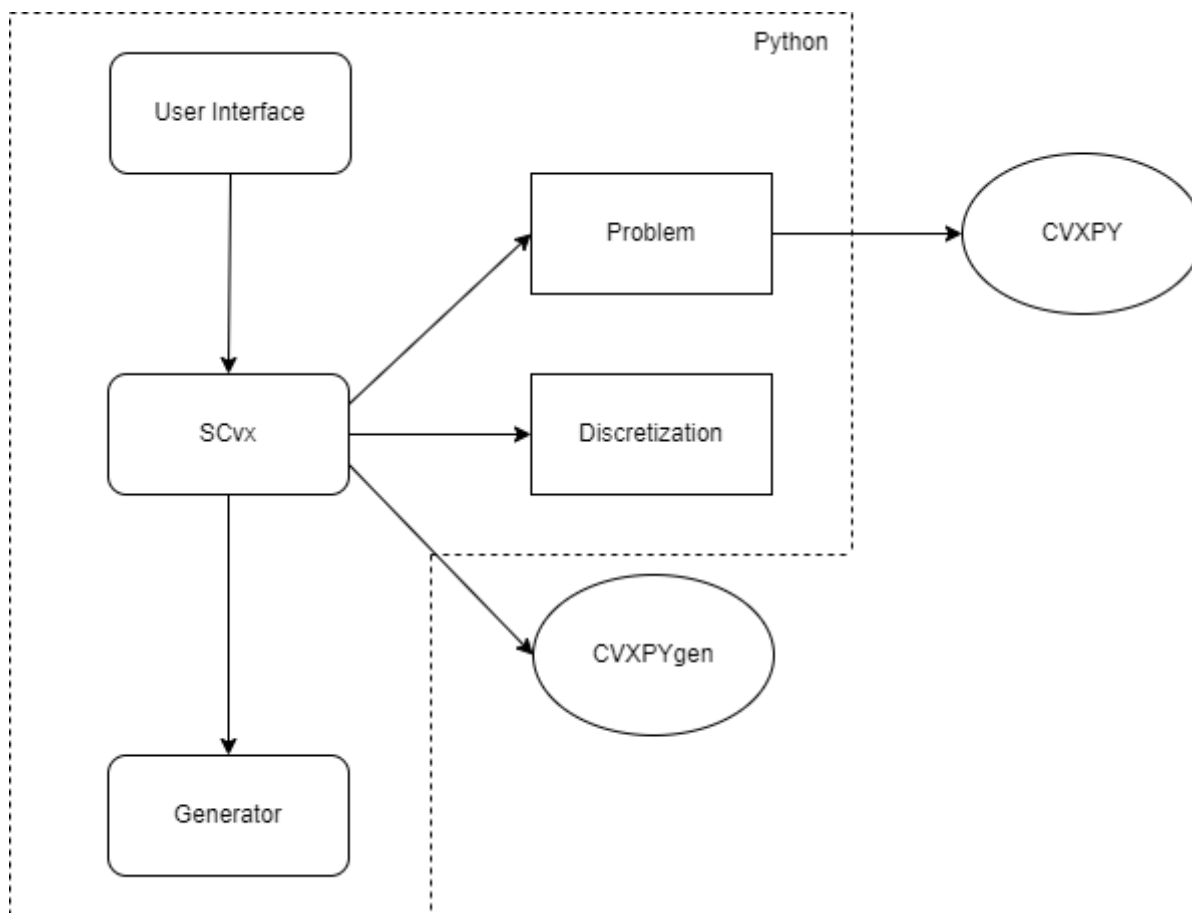
$$r - \frac{\left(x_k^{(i-1)} - p\right) \left(x_k^{(i)} - p\right)}{\|x_k^{(i-1)} - p\|_2 + 10^{-6}} < 0$$

becomes,

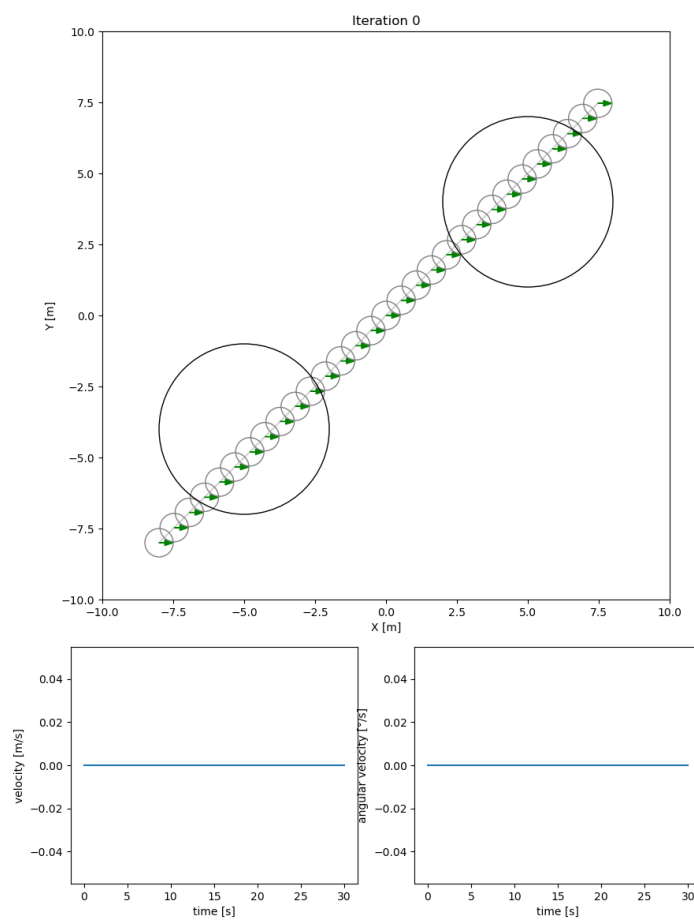
$$r - \left(\text{ObstacleParam}_k^{(i)} \left(x_k^{(i)} - p\right)\right) < 0$$

# Autocoding in C

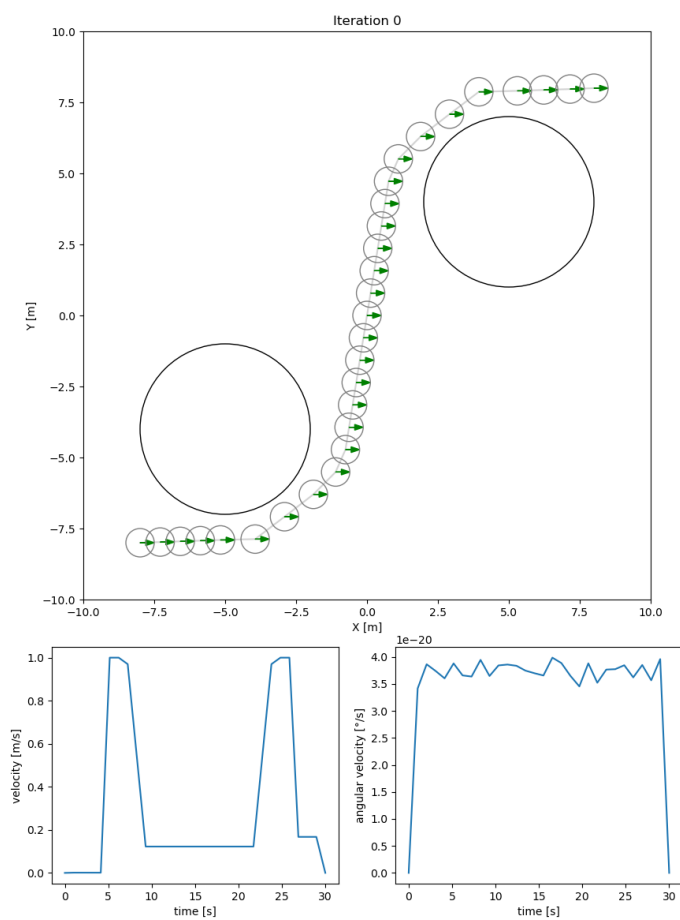
## Architecture



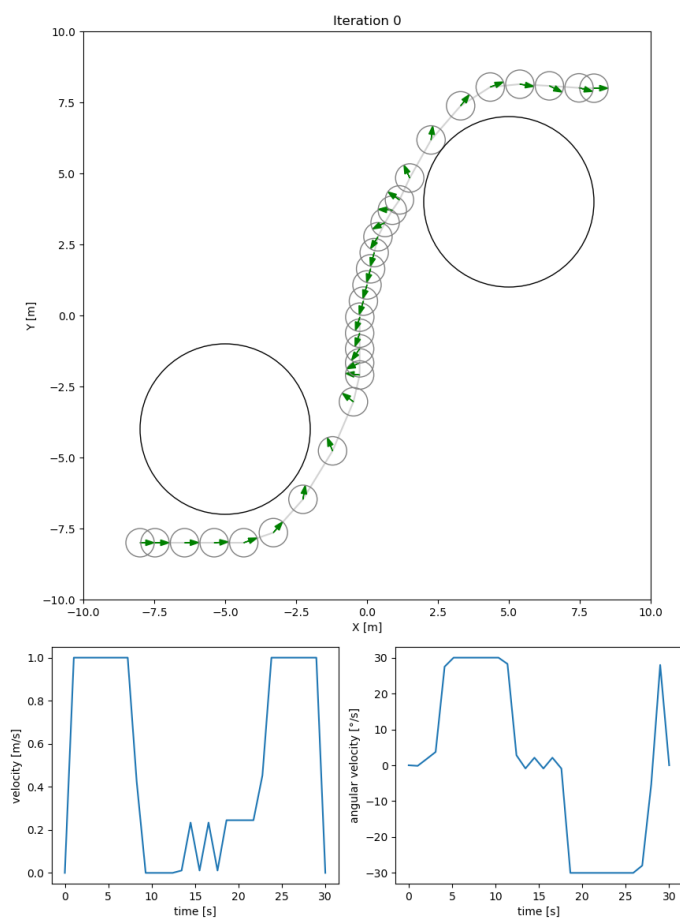
# Solution on example (C implem.) – iteration 0



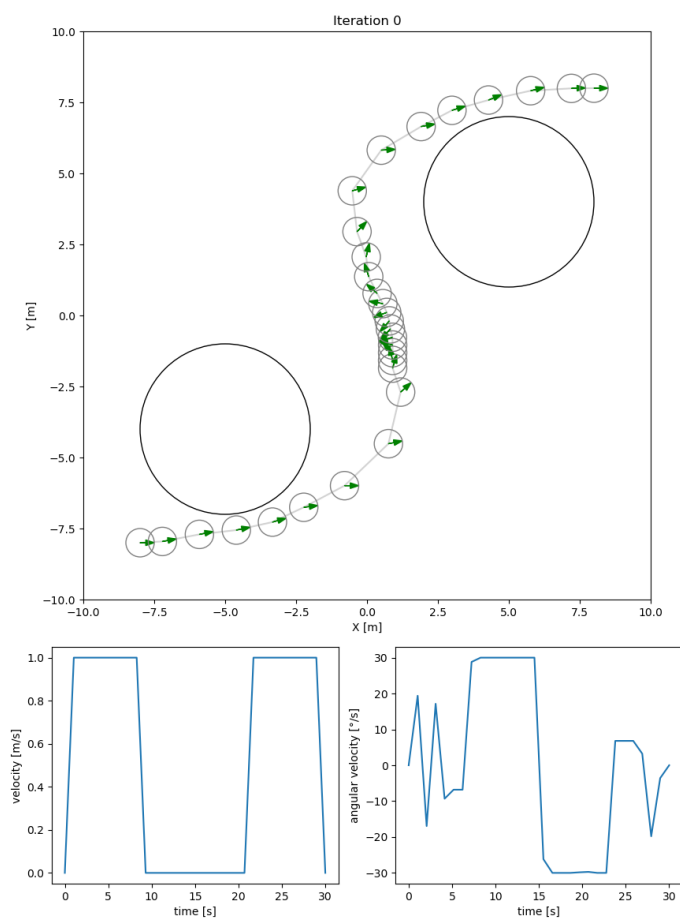
# Solution on example (C implem.) – iteration 1



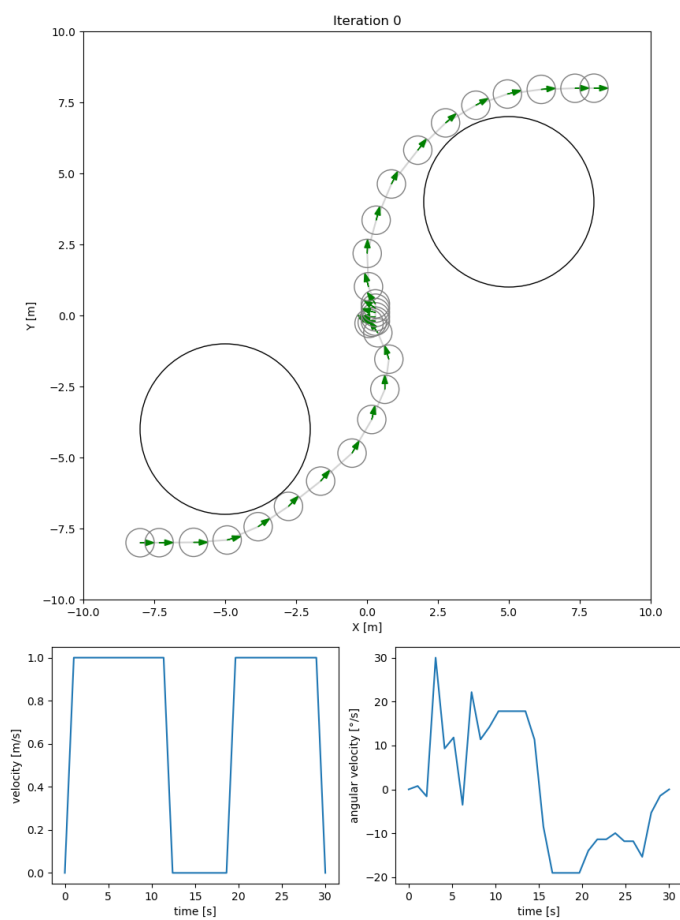
# Solution on example (C implem.) – iteration 2



# Solution on example (C implem.) – iteration 3

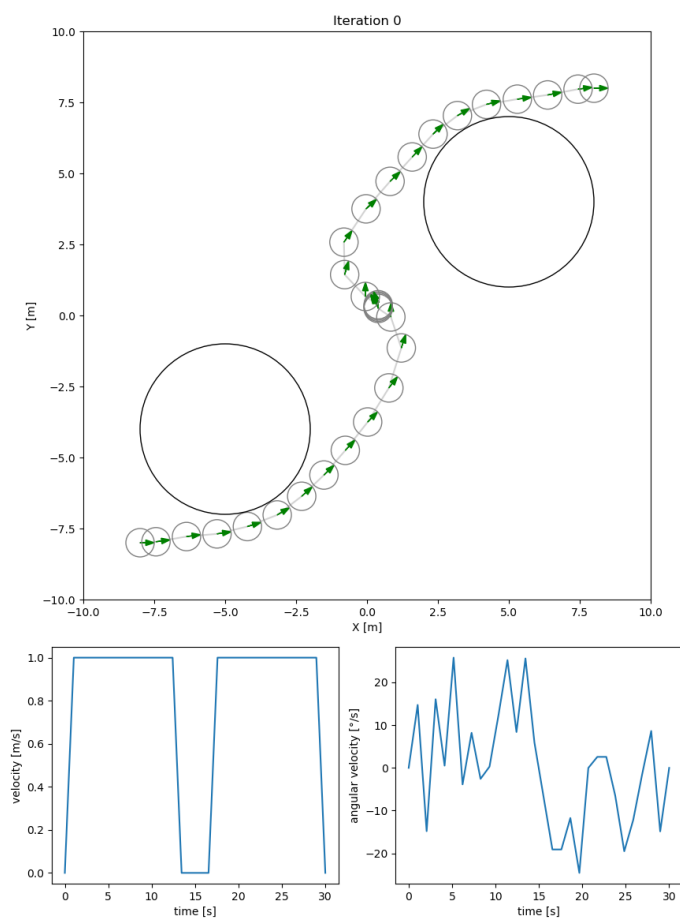


# Solution on example (C implem.) – iteration 4

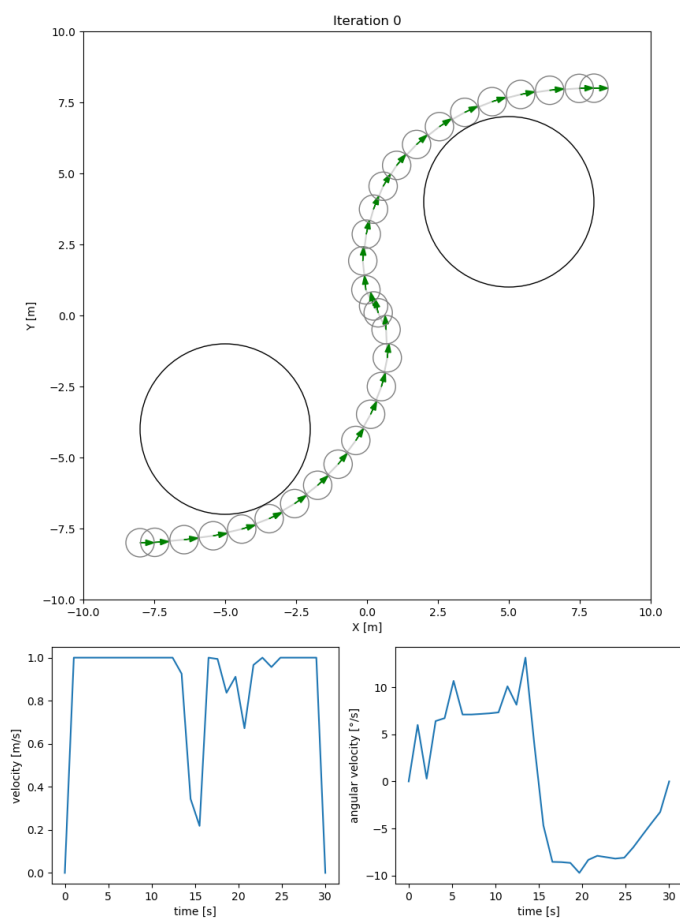




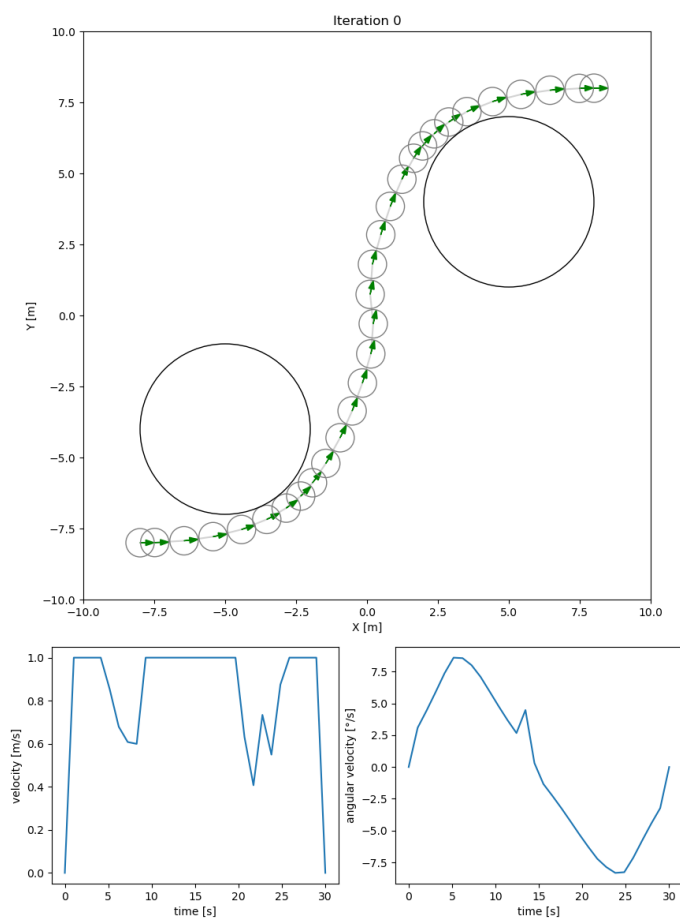
# Solution on example (C implem.) – iteration 5



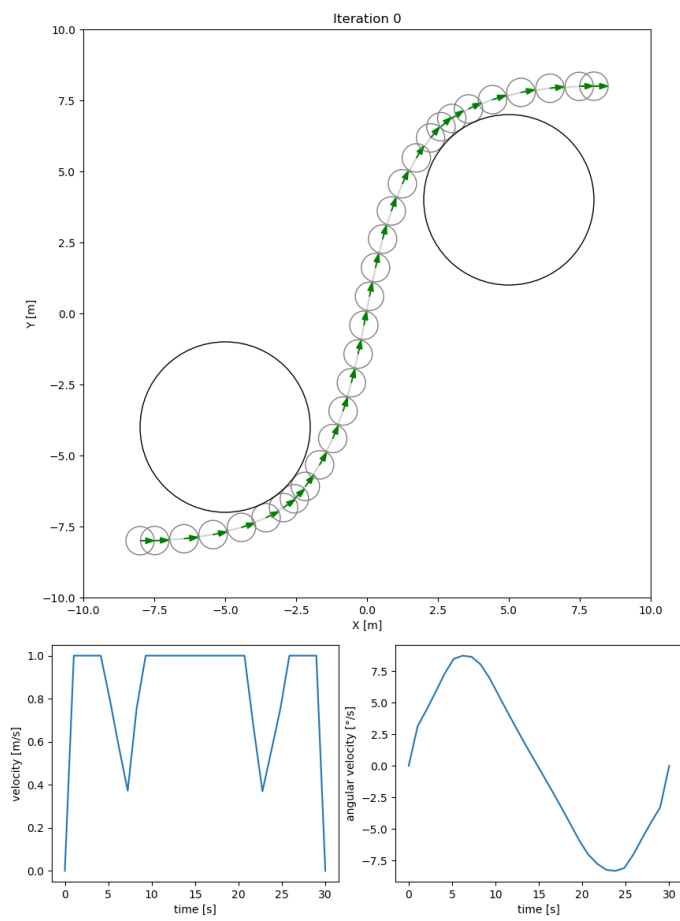
# Solution on example (C implem.) – iteration 6



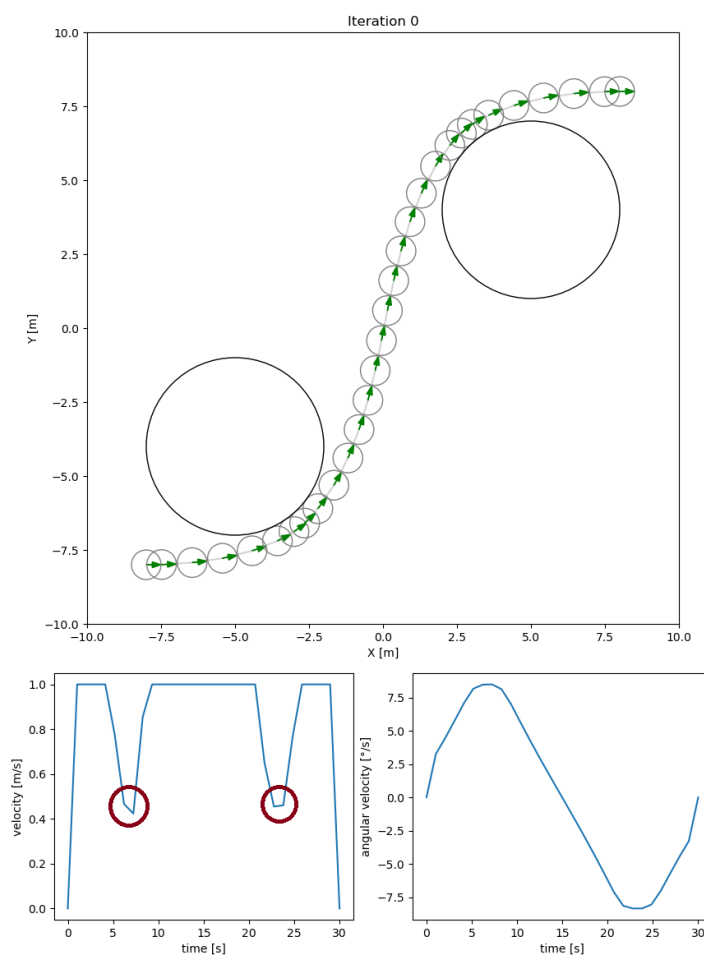
# Solution on example (C implem.) – iteration 7



# Solution on example (C implem.) – iteration 8



# Solution on example (C implem.) – iteration 9



## C code performance analysis

Command being timed: `./SCvx`

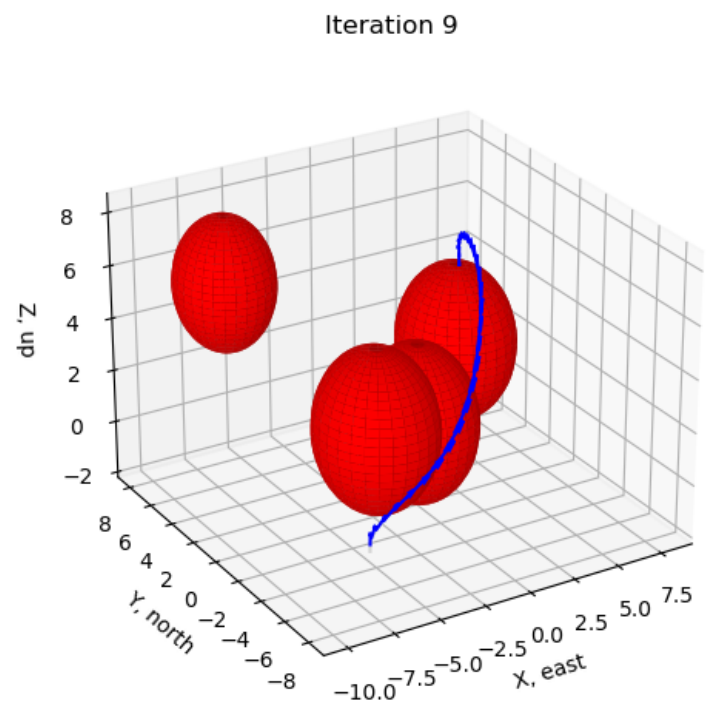
- User time (seconds): 0.88
- System time (seconds): 0.00
- Percent of CPU this job got: 100
- Elapsed (wall clock) time (h:mm:ss or m:ss): 0:00.88
- Maximum resident set size (kbytes): 5248

**Remarks:** embedded constraints may be met by this C code generator. A lot of improvements can be made to reduce memory consumption.

## Ongoing example



- 30 discretization points
- 8 secondes trajectory
- Avoids obstacles
- Ongoing work to automatically generate C code for 3D dynamics



## 1st Year summary

### What have been done on technical side?

- Implementation of SCvxPy
- Implementation of SCvxPyGen

### Next steps

- Continue testing on more complex examples
- Reduce memory consumption
- Implement this algorithm on real robots
- Plan missions using Temporal Logic

**Promoting results:** paper submission at ECC'24 (deadline October 25).



## Main uses of STL

Temporal logics specify patterns that timed behaviors of systems may or may not satisfy. Many flavors but we consider STL.

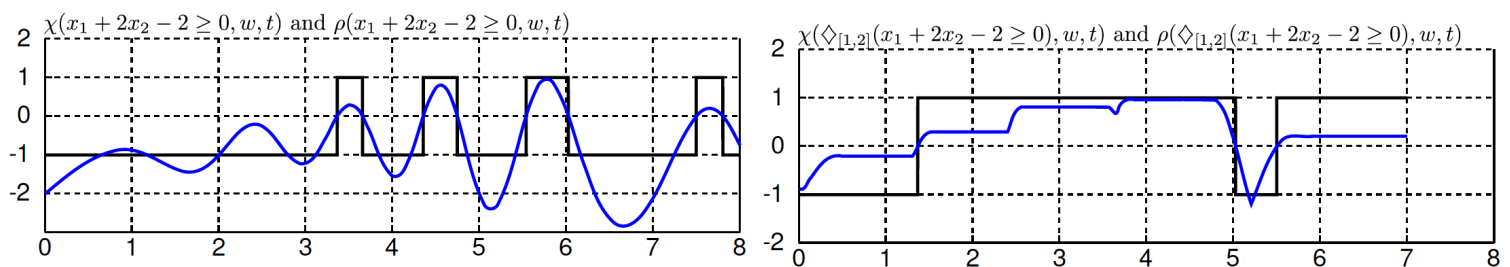
### STL formula example

Between 2s and 6s the signal is between  $-2$  and  $2$

$\phi := \text{Globaly}_{[2,6]} (|x(t)| < 2)$       Note: temporal modalities are bounded

STL is mainly used:

- to perform (offline/online) **monitoring**
- to perform **controller synthesis**



## Long term goal: integrate STL constraints into SCvx

### Non-convex Problem with STL constraints:

$$\underset{x_i, u_i}{\text{minimize}} \quad \sum_{i=1}^{t_f} \phi(x_i, u_i),$$

subject to

$$x_{i+1} = f(x_i, u_i) \quad i = 1, 2, \dots, t_f - 1,$$

$$s(x_i) \leq 0 \quad i = 1, 2, \dots, t_f,$$

$$u_i \in U_i, x_i \in X_i \quad i = 1, 2, \dots, t_f - 1,$$

$$(x, u) \models \varphi$$

What should be done

- A PoC has been done<sup>2</sup> **but need to automatize the linearization**
- **Manage nested temporal logic operator of STL**

<sup>2</sup>SCVx for Optimal Control with STL Specifications, Mao *et al.*, HSCC'22

## References

-  Y. Mao, M. Szmuk, and B. Acikmese, “Successive convexification of non-convex optimal control problems and its convergence properties,” in 2016 IEEE 55th Conference on Decision and Control (CDC). IEEE, dec 2016.
-  A. Domahidi, E. Chu, and S. Boyd, “ECOS: An SOCP solver for embedded systems,” in 2013 European Control Conference (ECC). IEEE, Jul. 2013.
-  A. Agrawal, R. Verschueren, S. Diamond, and S. Boyd, “A rewriting system for convex optimization problems,” *Journal of Control and Decision*, vol. 5, no. 1, pp. 42–60, 2018.
-  M. Schaller, G. Banjac, S. Diamond, A. Agrawal, B. Stellato, and S. P. Boyd, “Embedded code generation with CVXPY,” *IEEE Control. Syst. Lett.*, vol. 6, pp. 2653–2658, 2022.
-  Yuanqi Mao, Behcet Acikmese, Pierre-Loïc Garoche, Alexandre Chapoutot. Successive Convexification for Optimal Control with Signal Temporal Logic Specifications. 25th ACM International Conference on Hybrid Systems: Computation and Control (HSCC '22), May 2022, Milan, Italy. 10.1145/3501710.3519518. hal-03663984f