6-Axis Robot

5-Step-SARSA

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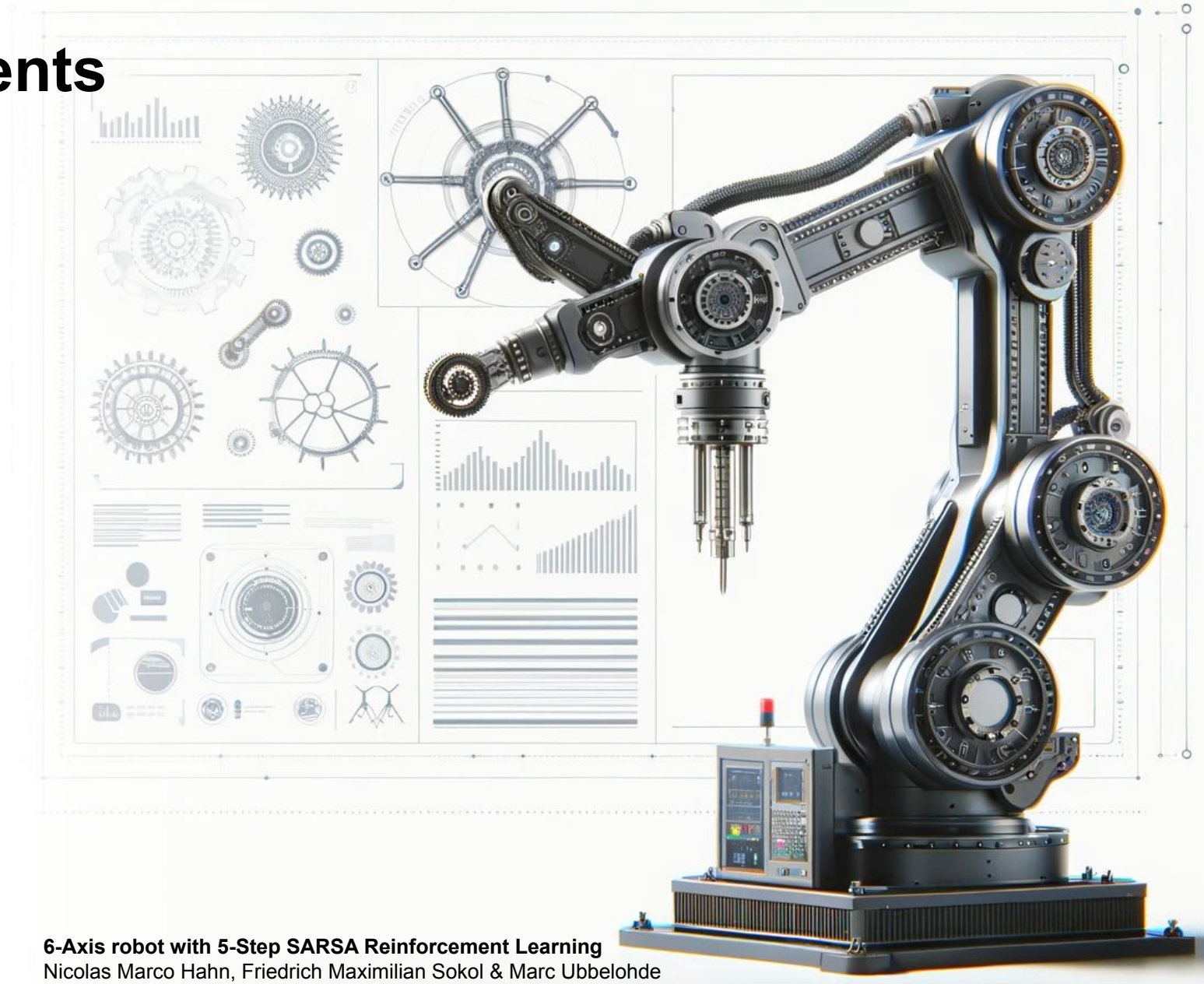
für Technik

Studiere Zukunft

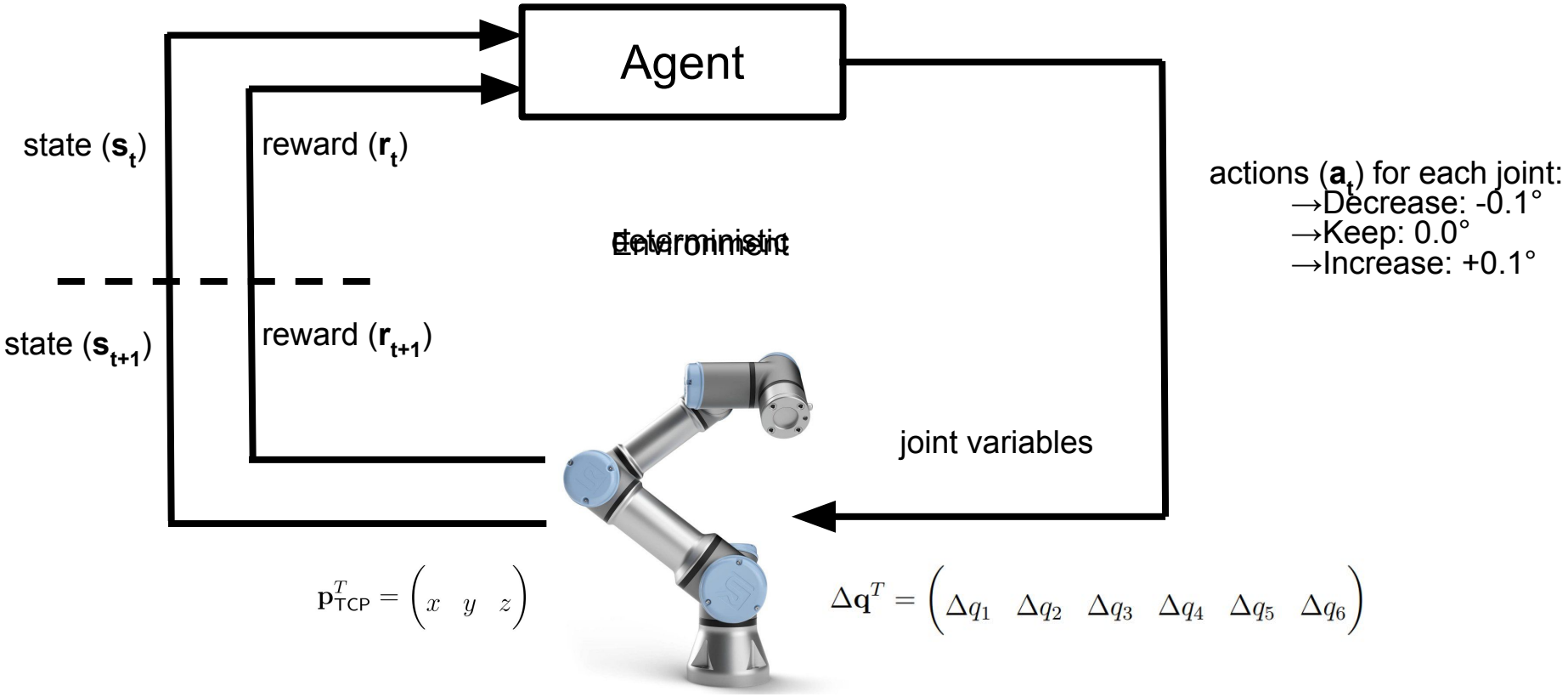
Table of Contents

- Task
- Environment
- Trajectory
- Algorithm
- Approaches
- Results
- Future Work



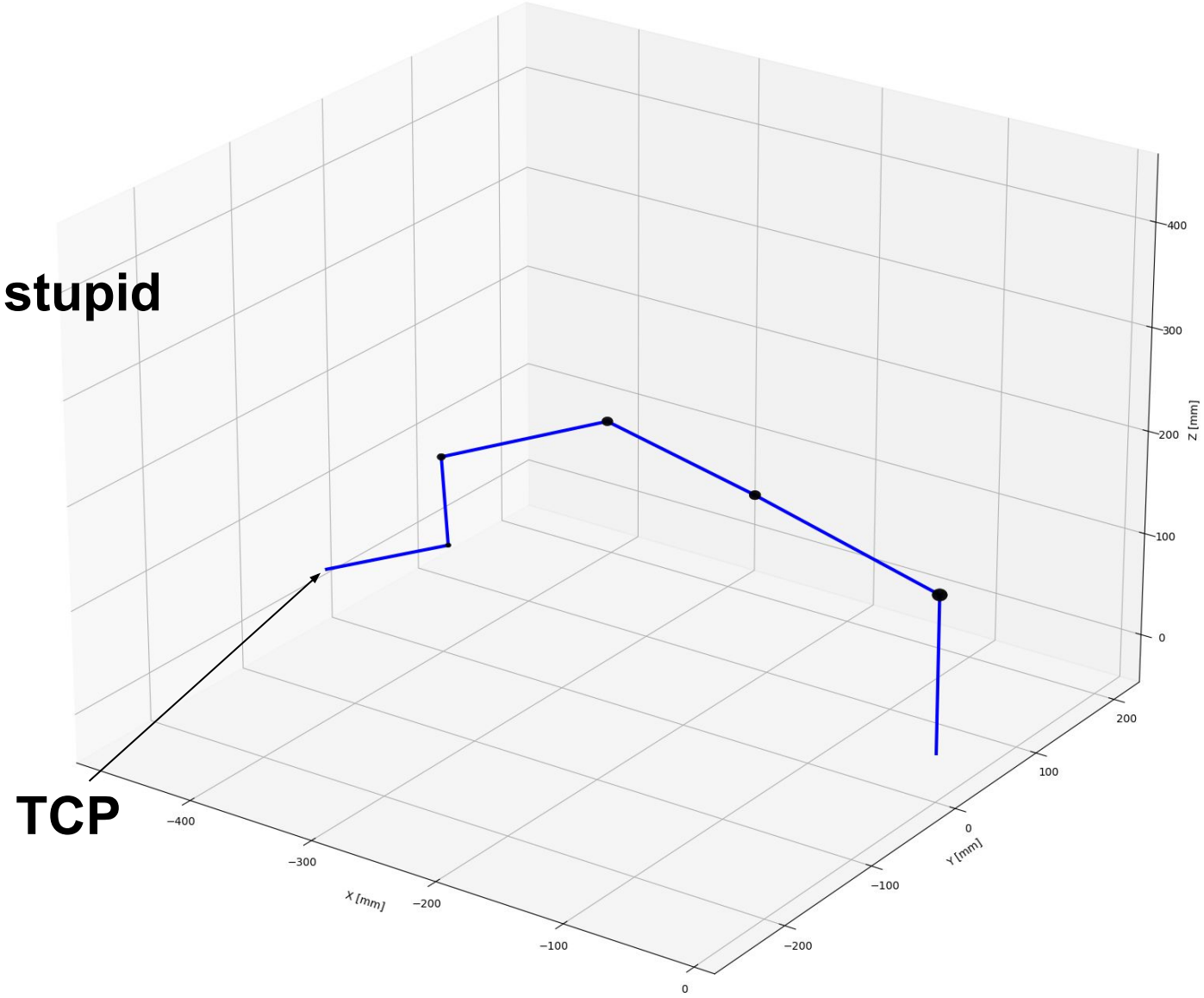
Source: Dall-E

Task


Agent
state ($\mathbf{s}_t$)
reward ($\mathbf{r}_t$)
Environment
deterministic
state ($\mathbf{s}_{t+1}$)
reward ($\mathbf{r}_{t+1}$)
actions ($\mathbf{a}_t$) for each joint:
→Decrease: -0.1°
→Keep: 0.0°
→Increase: +0.1°
joint variables
$\mathbf{p}_{\mathrm{TCP}}^T = \begin{pmatrix} x & y & z \end{pmatrix}$
$\Delta\mathbf{q}^T = \begin{pmatrix} \Delta q_1 & \Delta q_2 & \Delta q_3 & \Delta q_4 & \Delta q_5 & \Delta q_6 \end{pmatrix}$

Environment

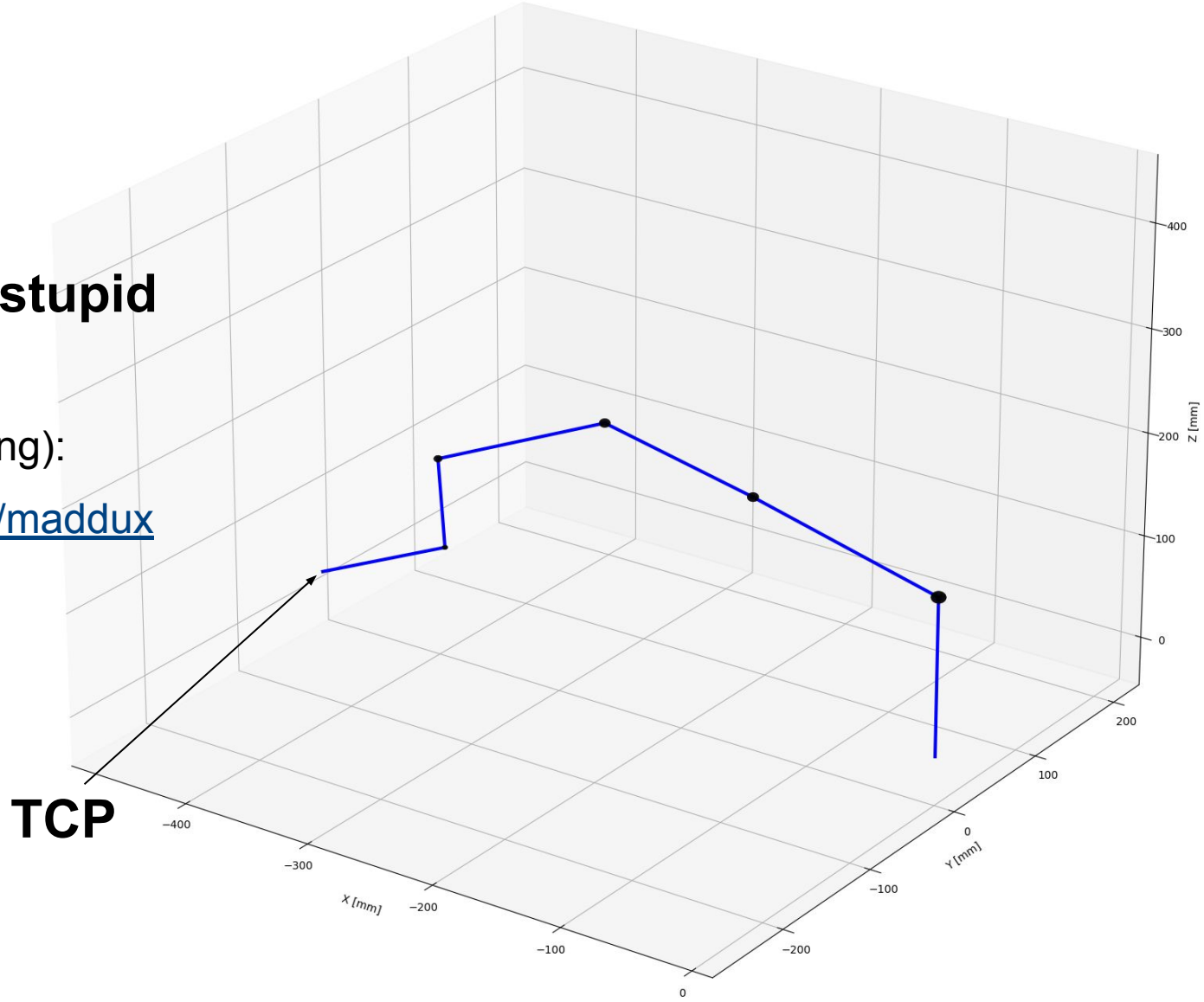
KISS-Principle: Keep it simple (and) stupid



Environment

KISS-Principle: Keep it simple (and) stupid

- Robot simulation (forward kinematics and plotting):
  - adapted version of https://github.com/bcaine/maddux



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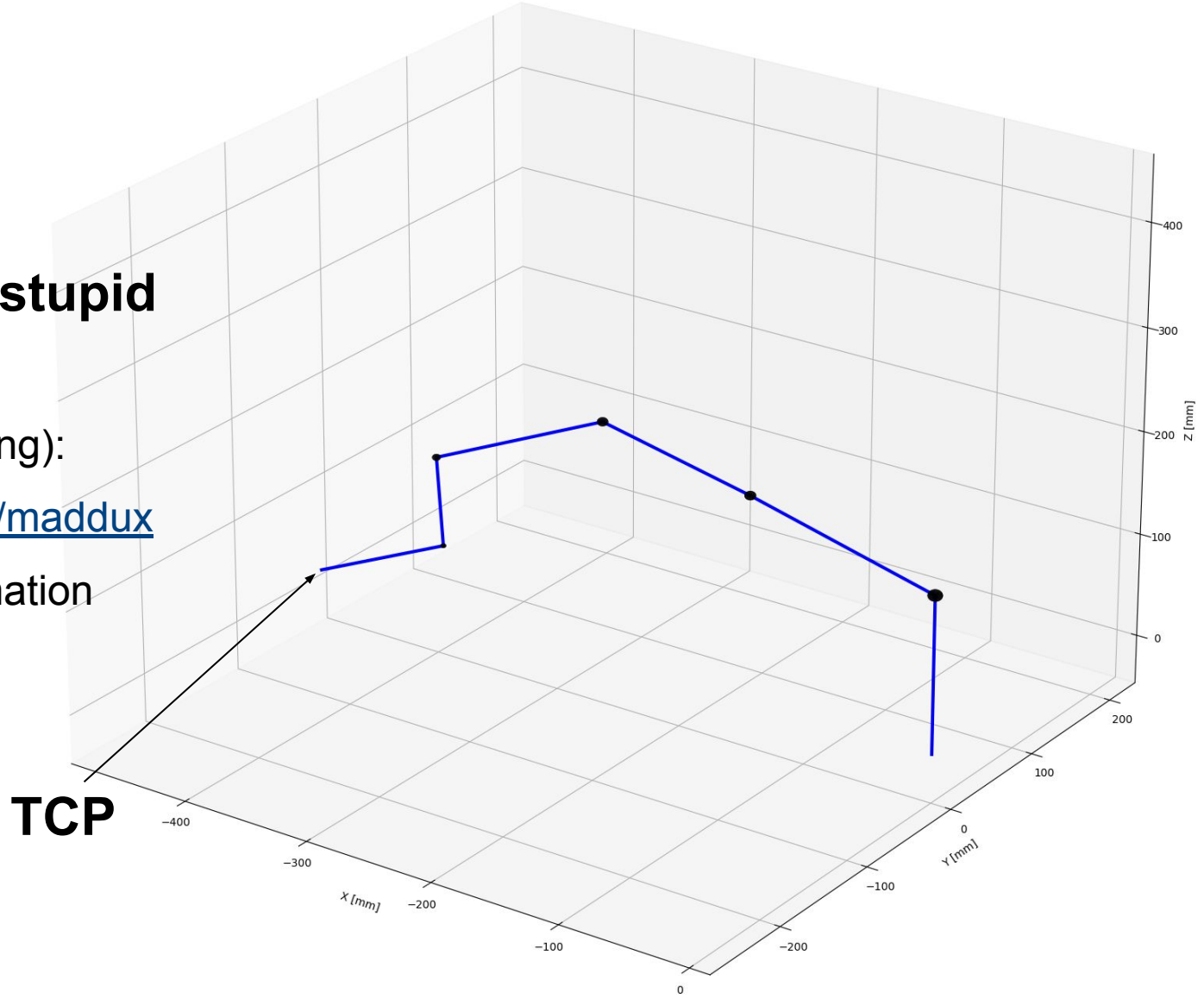
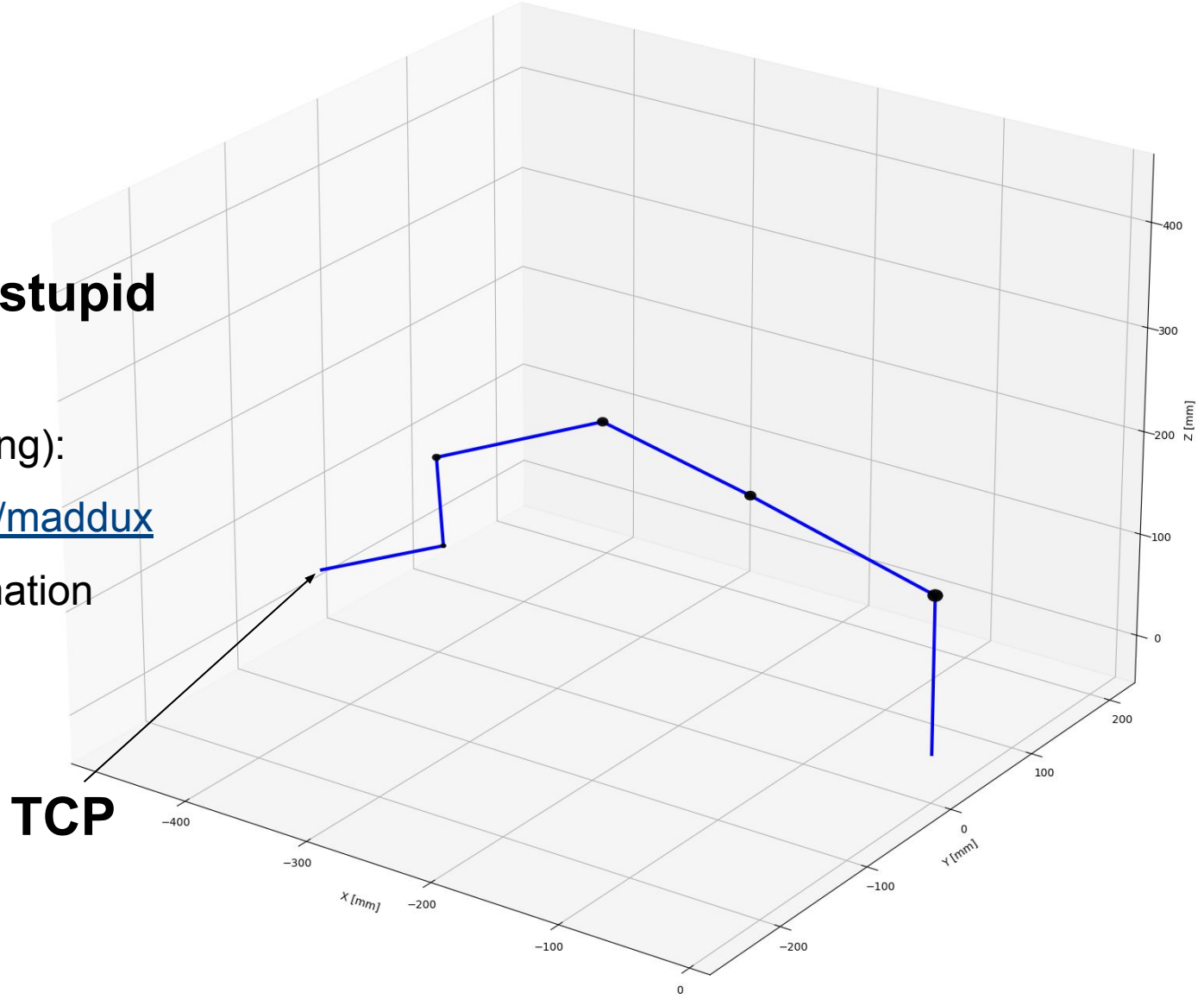
- Use matplotlib for light weight plotting and animation



Environment

KISS-Principle: Keep it simple (and) stupid

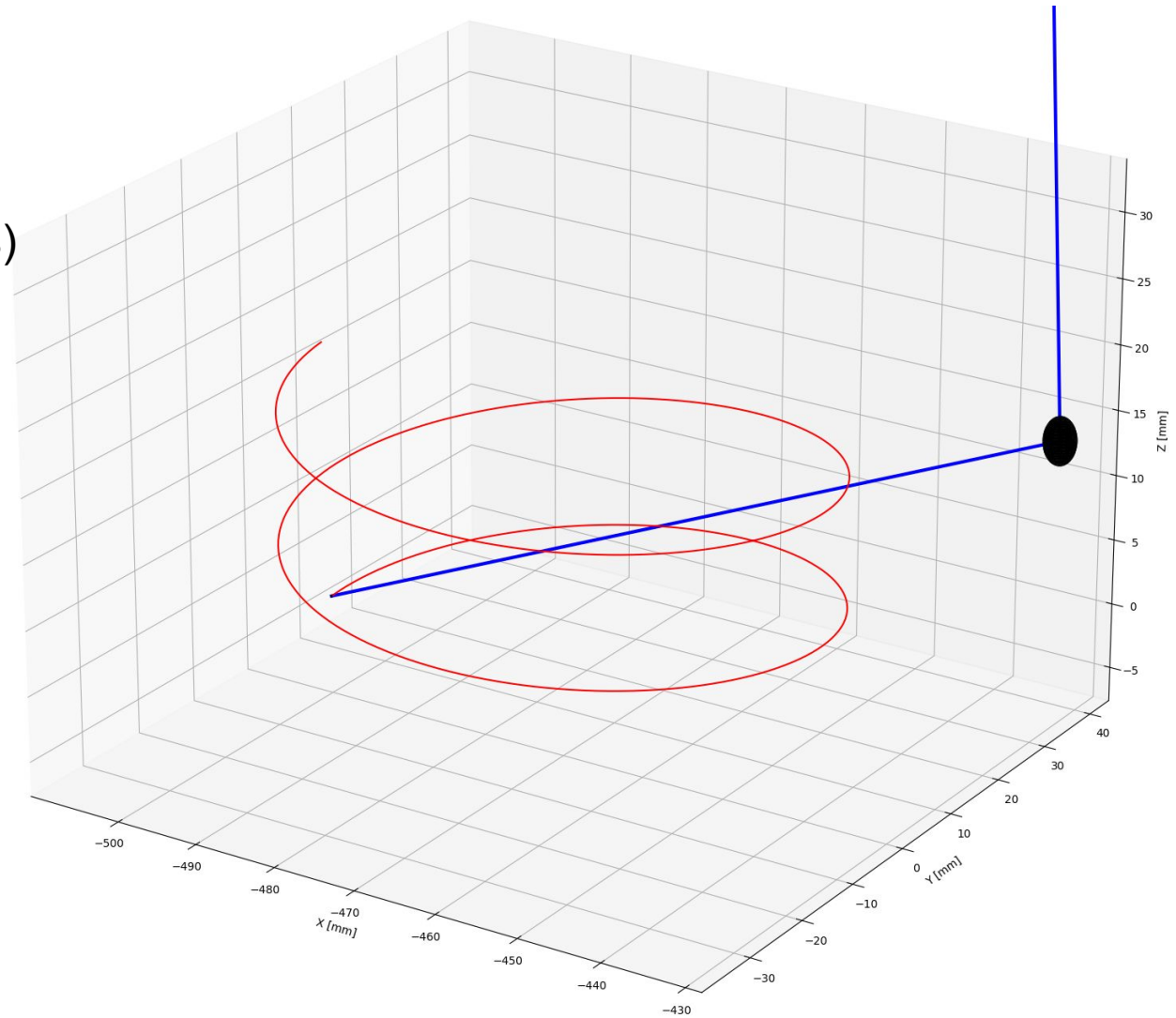
- Robot simulation (forward kinematics and plotting):
  - adapted version of https://github.com/bcaine/maddux
- Use matplotlib for light weight plotting and animation
- Wrapper around robot simulation:
  - get reward, get TCP
  - do move, check win etc.



Trajectory

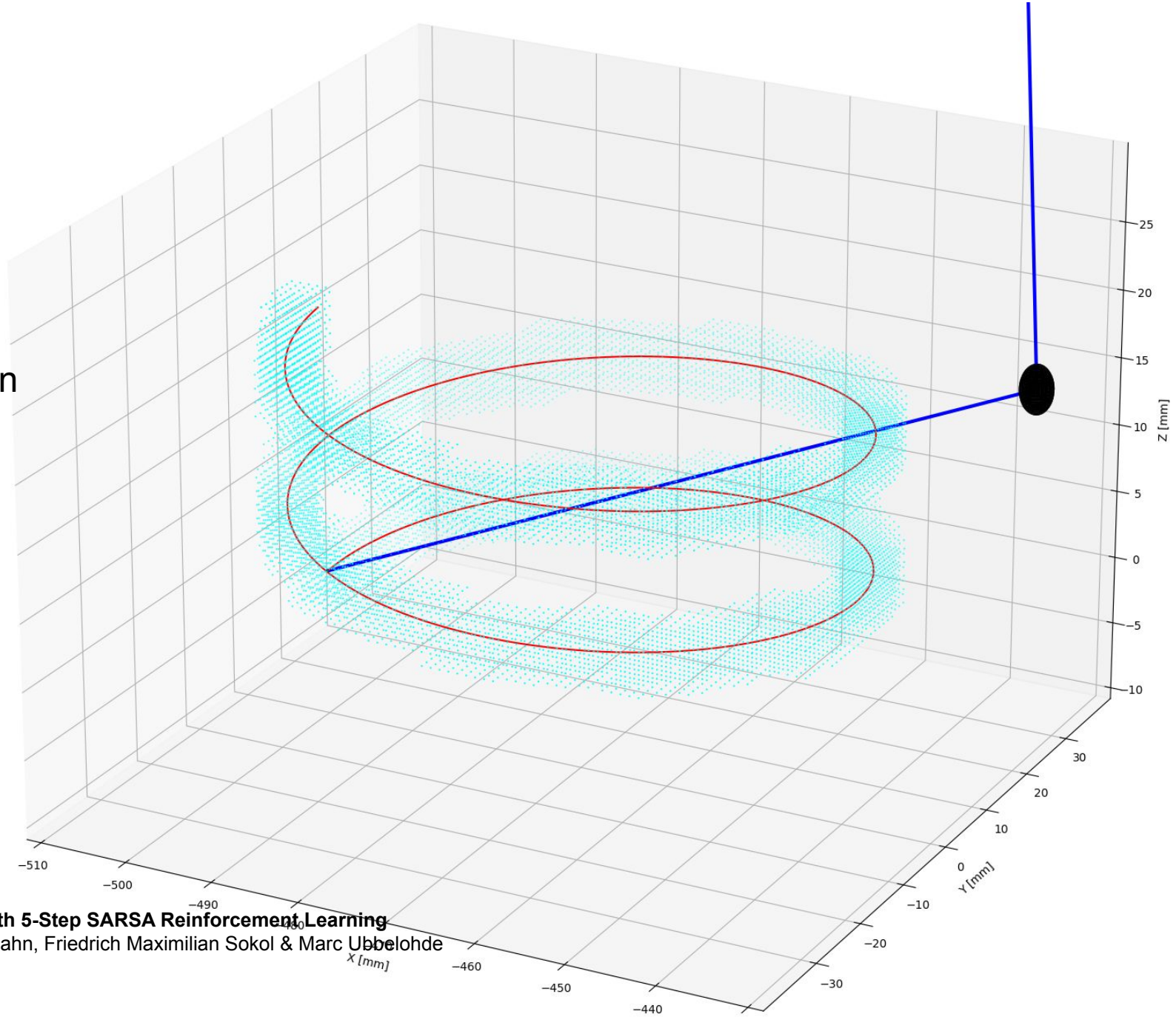
- Helix with radius 3 cm and a height of 2 cm (2 turns)
- Generated as a set of 300 x, y, z coordinates

$$\begin{pmatrix} x(t) \\ y(t) \\ z(t) \end{pmatrix} = \begin{pmatrix} -3 \cdot \cos(4\pi t) + 3 + x_{\text{start}} \\ 3 \cdot \sin(4\pi t) + y_{\text{start}} \\ 2 \cdot t + z_{\text{start}} \end{pmatrix}$$



Trajectory

- Voxellated space needed:
  - Q values
  - Reward specific to voxel position
  - “Winning Voxels”



Trajectory

- Voxellated space needed:
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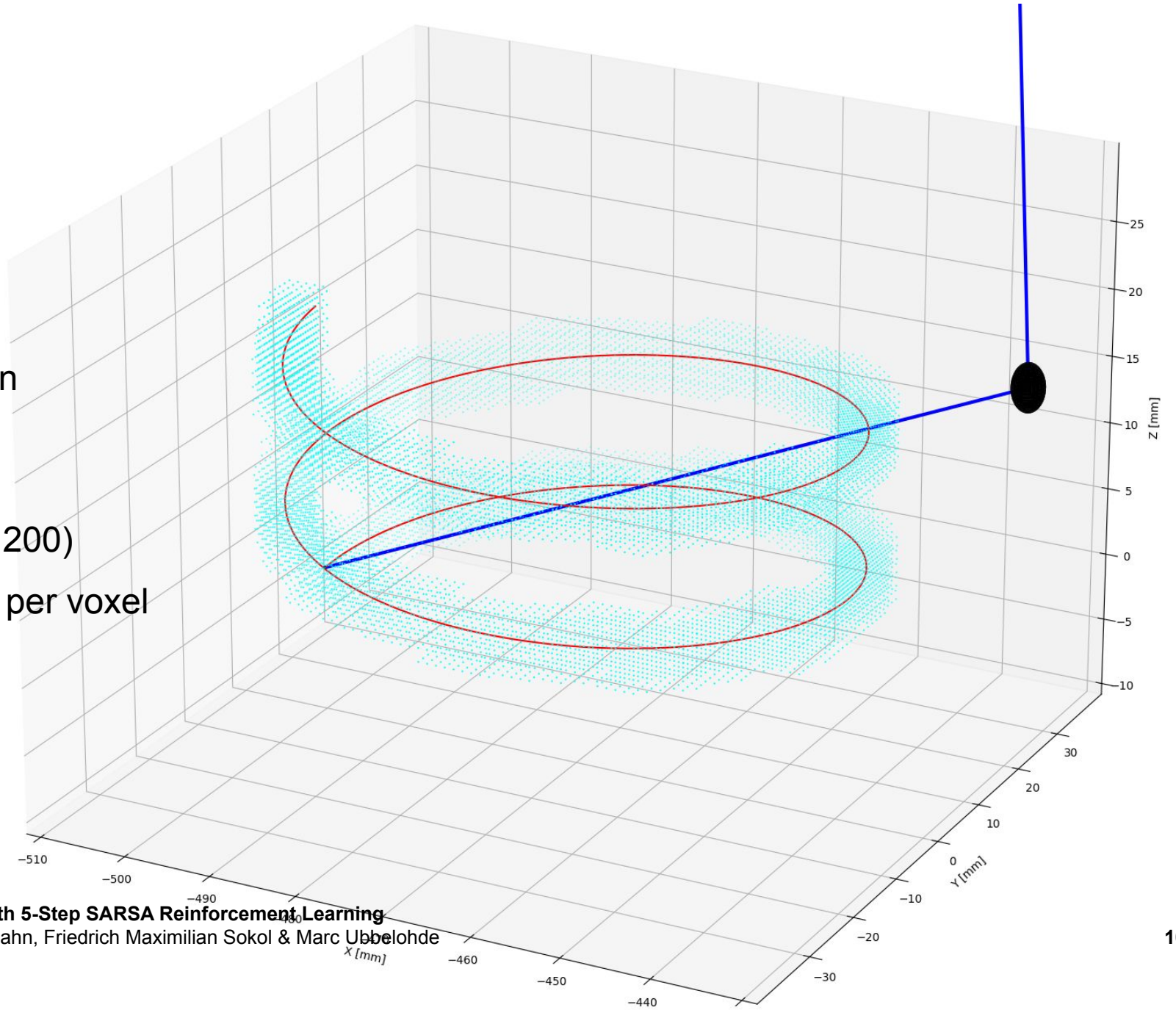
  - “Winning Voxels”

- Cube of voxels? (e.g. 600 x 600 x 200)

  = 72 × 10^6 voxels × 729 actions per voxel

  = 52.488 × 10^9 fields × 4

  = 209.952 TB of Data



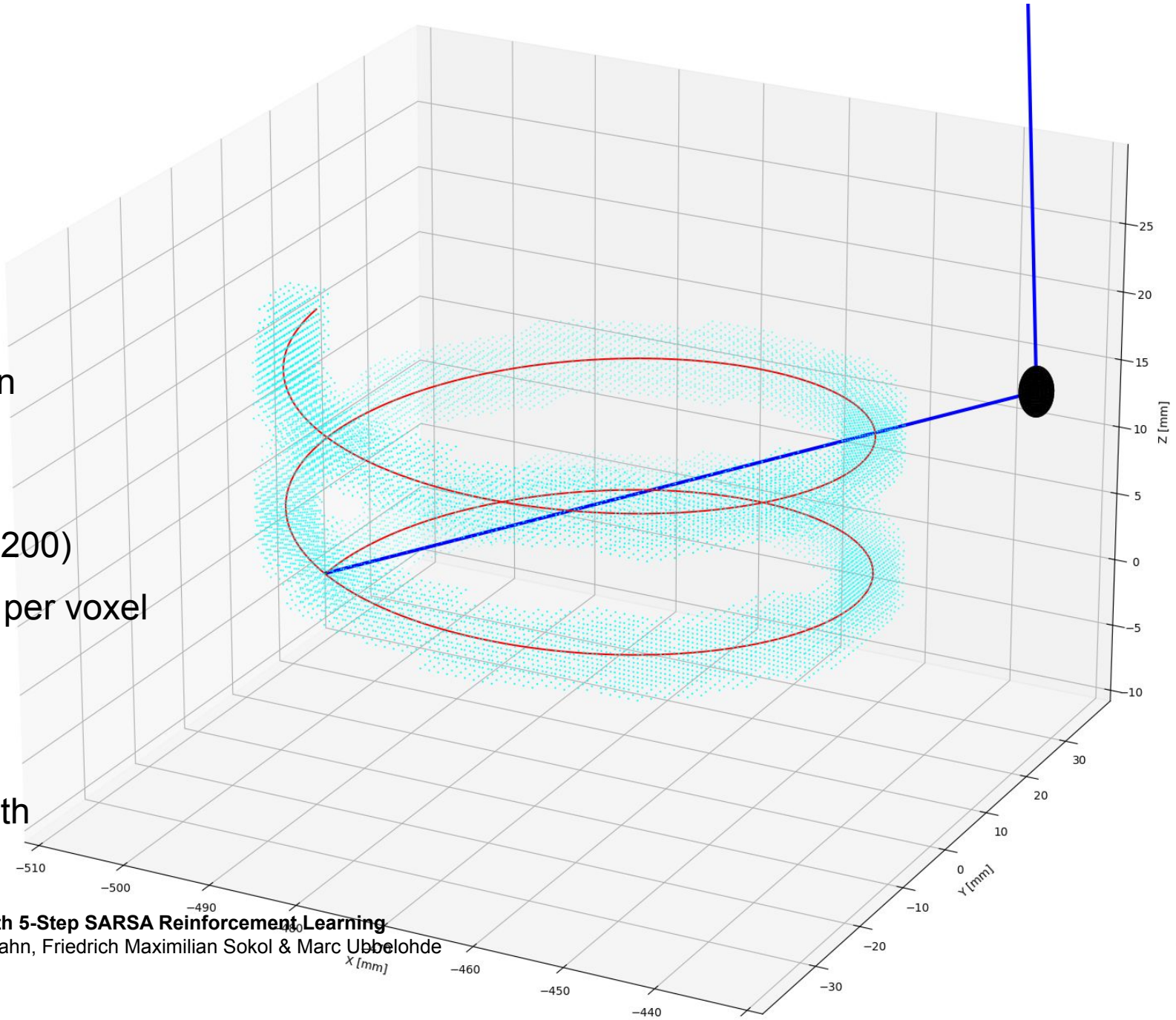
Trajectory

- Voxellated space needed:
  - Q values
  - Reward specific to voxel position
  - “Winning Voxels”
- Cube of voxels? (e.g. 600 x 600 x 200)

  = 72 × 10^6 voxels × 729 actions per voxel

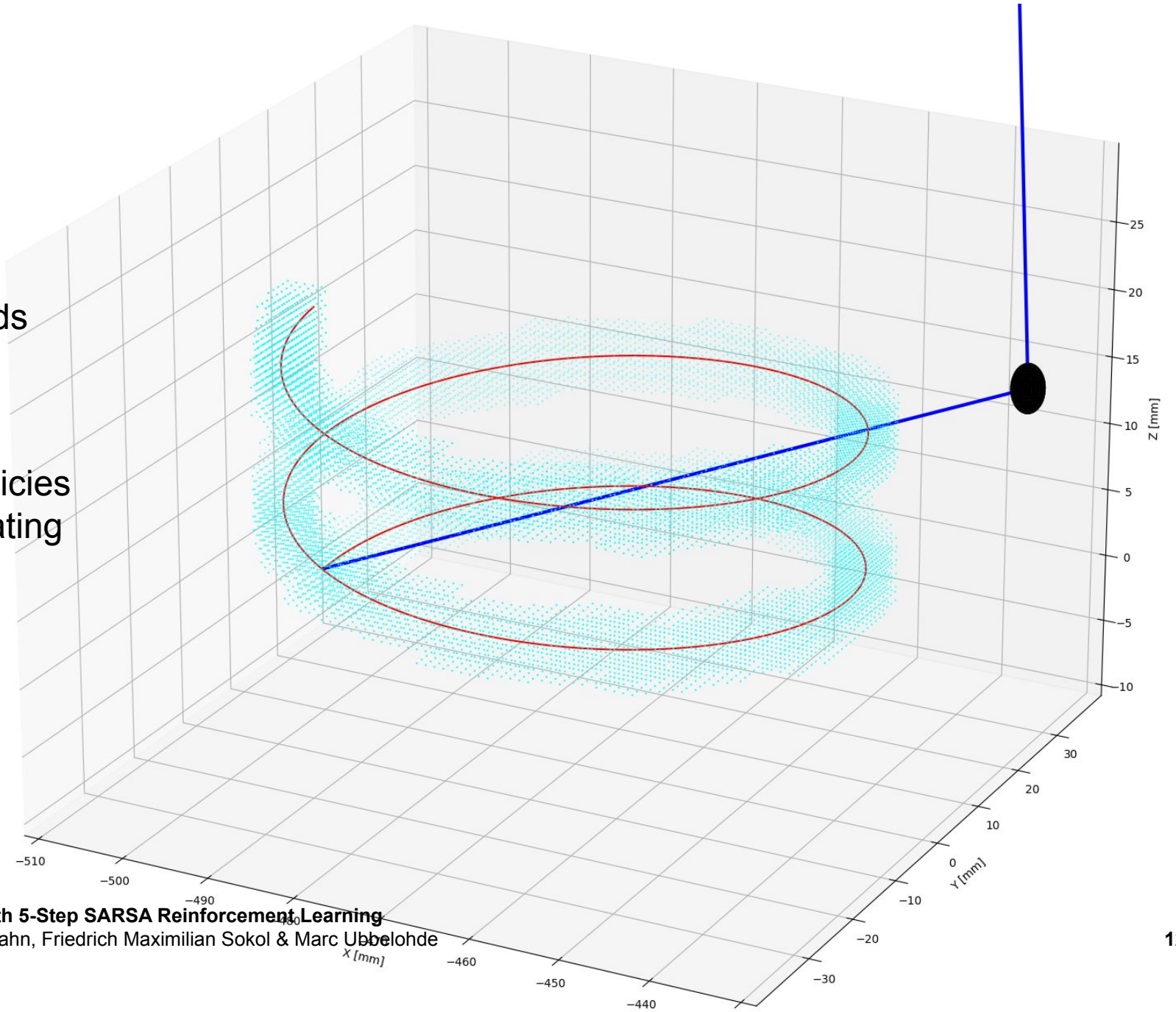
  = 52.488 × 10^9 fields × 4

  = 209.952 TB of Data
- →Only voxellate space around path



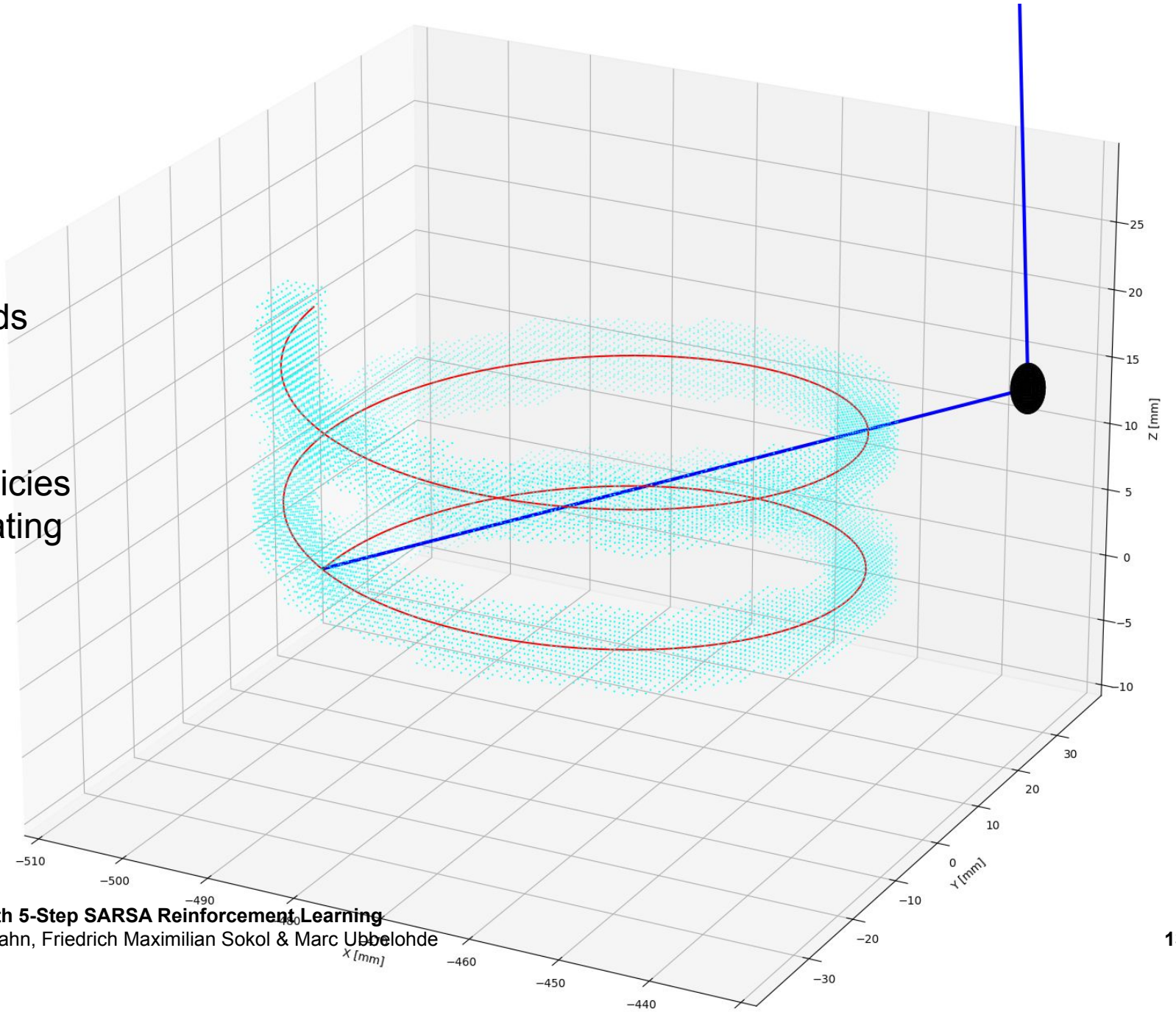
Trajectory

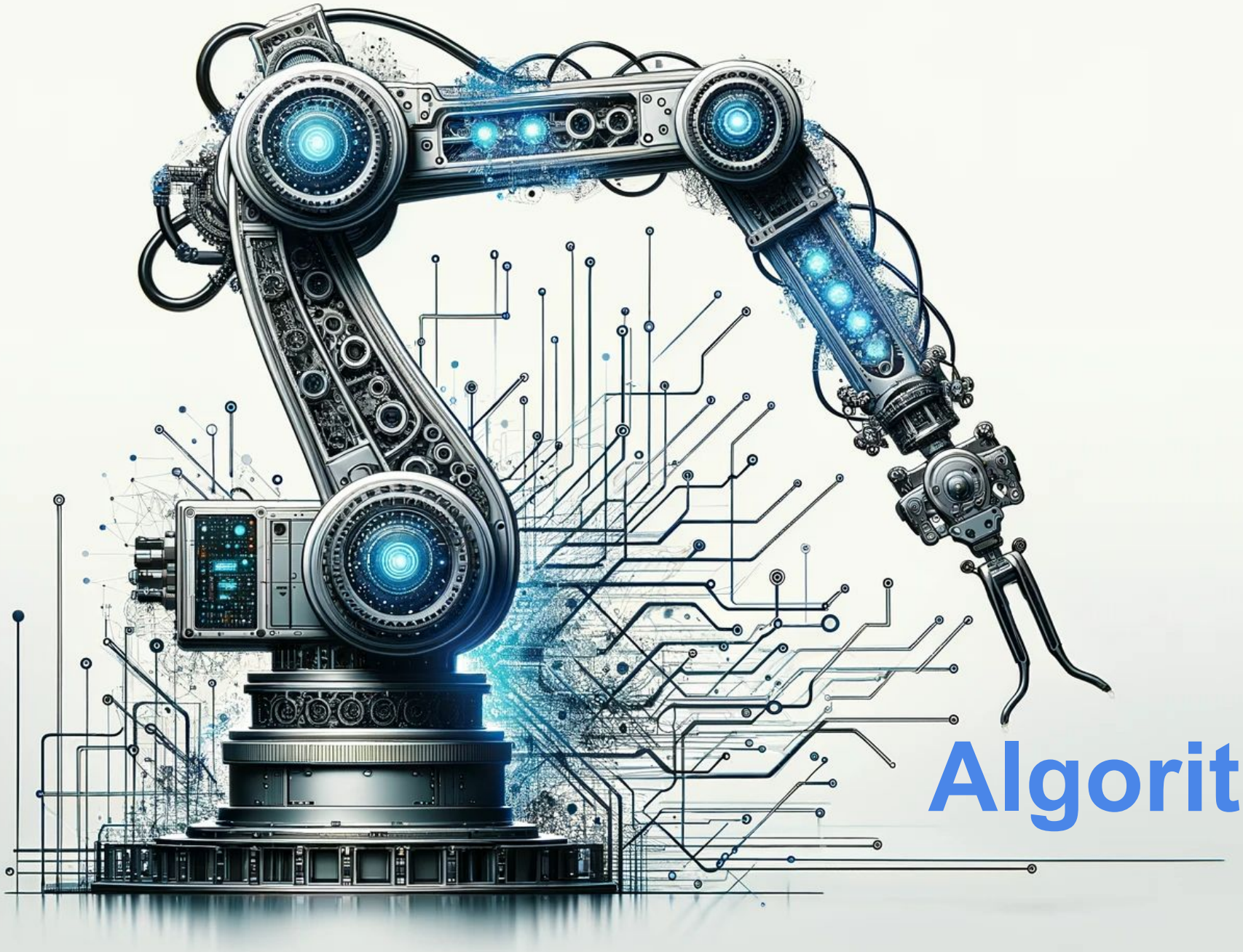
- Voxels generated before training
- Q values and voxel specific rewards in separate lists
- Voxel generates hash
  - used in hashmap containing indicies of each Q value / reward correlating to the Voxel



Trajectory

- Voxels generated before training
- Q values and voxel specific rewards in separate lists
- Voxel generates hash
  - used in hashmap containing indicies of each Q value / reward correlating to the Voxel
- No search algorithm needed
  - ⇒ Access time O(1)





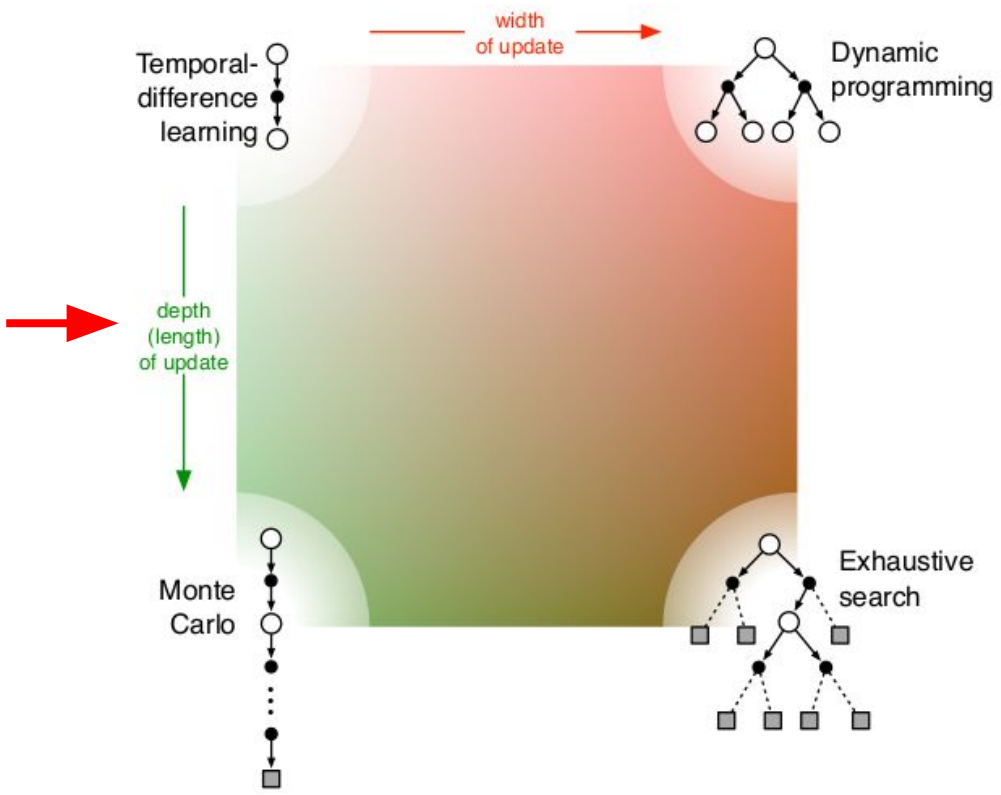
Algorithm

Source: Dall-E

Overview

n-step TD methods

- Different approaches to solve RL problems
- Graph have two axis which separate the algorithm
- Right: access to the model
- Left: looks at one trajectory, no model, sampling
- Upper: one step into the future
- Lower: until the end of the episode
- N-step-bootstrapping

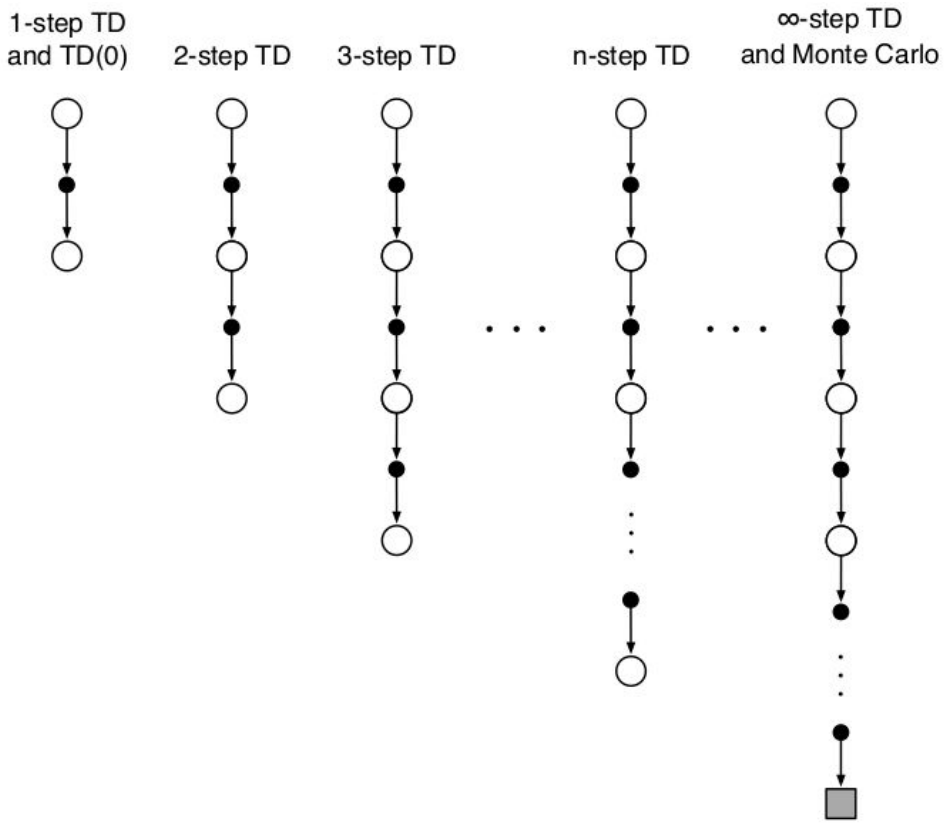


[1] Richard S. Sutton and Andrew g. Barto: Reinforcement Learning

Overview

n-step TD methods

- Two extremes: Temporal Difference and Monte Carlo
- Temporal Difference: information propagate slowly backwards
- Monte Carlo: updates are noisier
- Best methods are between: N-step-methods
- Bootstrapping works best with significant state change
- Look N-steps into the future
- Taking N-rewards into account (appropriately discounting)



[1] Richard S. Sutton and Andrew g. Barto: Reinforcement Learning

Implementation

5-Step-Sarsa

1) Input and output:

Transition-Probability-Function

Input: MDP $M = \langle S, s_0, A, P_a(s' \mid s), r(s, a, s') \rangle$, number of steps n

Output: Q-function Q

Initialise Q arbitrary; e.g., $Q(s, a) = 0$ for all s and a

Action-Value-Function

2) Iterate over episodes:

Repeat (for each episode)

agent acts greedy but we also need exploration

Select action a to apply in s using Q-values in Q and a multi-armed bandit algorithm such as ϵ-greedy

$ss = \langle s \rangle$

$as = \langle a \rangle$ store states, rewards and actions

$rs = \langle \rangle$

Implementation

5-Step-Sarsa

3) Interact with environment and store experience:

While ss is not empty

If s is not a terminal state then:

Execute action a in state s

Observe reward r and new state s'

$rs \leftarrow rs + \langle r \rangle$ add received reward to reward list

If s' is not a terminal state then:

Select action a' to apply in s' using Q and a multi-armed bandit algorithm

$ss \leftarrow ss + \langle s' \rangle$

$as \leftarrow ss + \langle a' \rangle$ add new state and actions to the lists

Implementation

5-Step-Sarsa

4) Learning from experience:

learning begins if reward list has a length of 5

If $|rs| = n$ or s is a terminal state then:

$G \leftarrow \sum_{i=0}^{|rs|-1} \gamma^i rs_i$

If s is not a terminal state then: $G \leftarrow G + \gamma^n Q(s', a')$

$Q(ss_0, as_0) \leftarrow Q(ss_0, as_0) + \alpha[G - Q(ss_0, as_0)]$ calculate the new action-value

$rs \leftarrow rs_{[1:n+1]}$

$ss \leftarrow ss_{[1:n+1]}$ delete everything which is older then 5 steps in the past

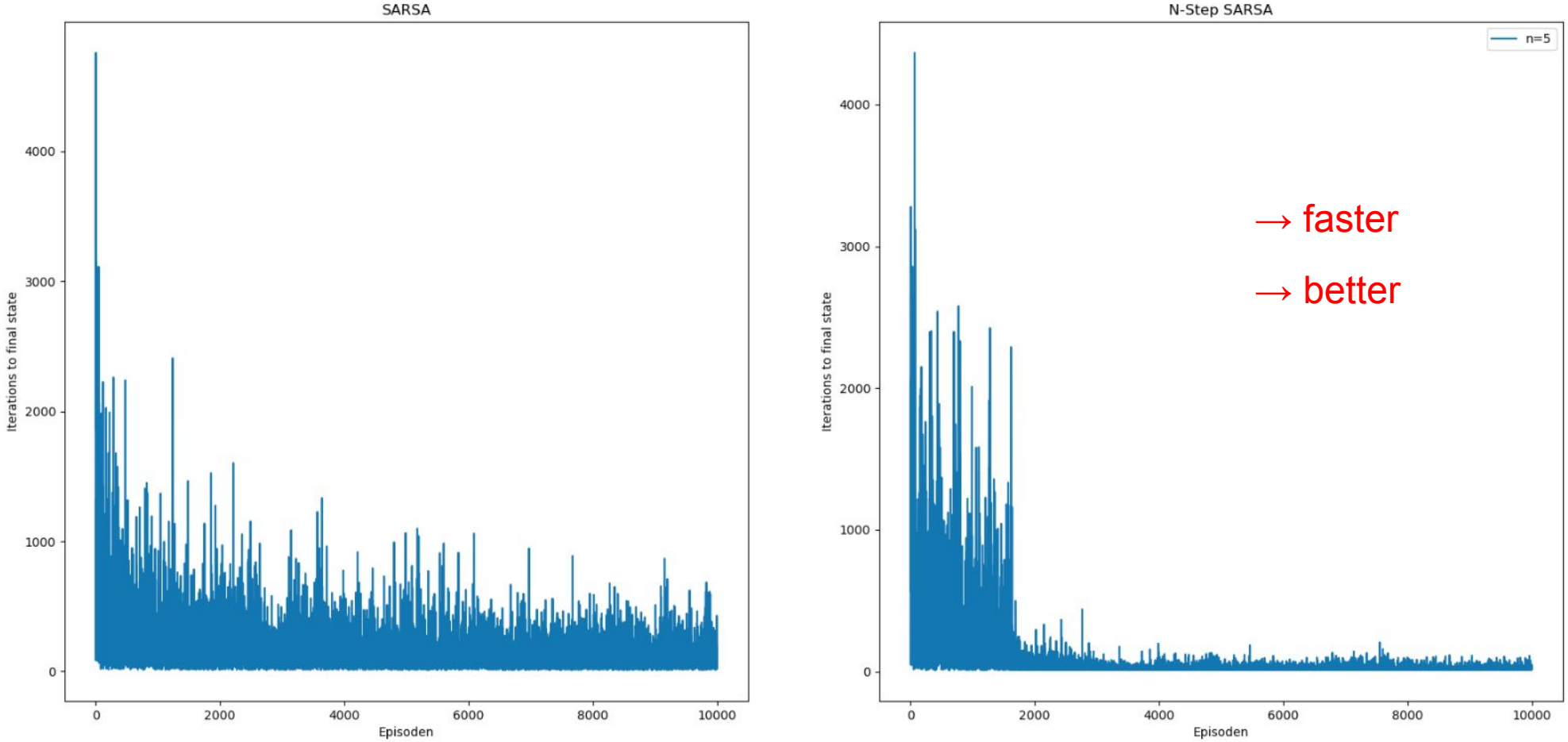
$as \leftarrow as_{[1:n+1]}$

$s \leftarrow s'$

$a \leftarrow a'$

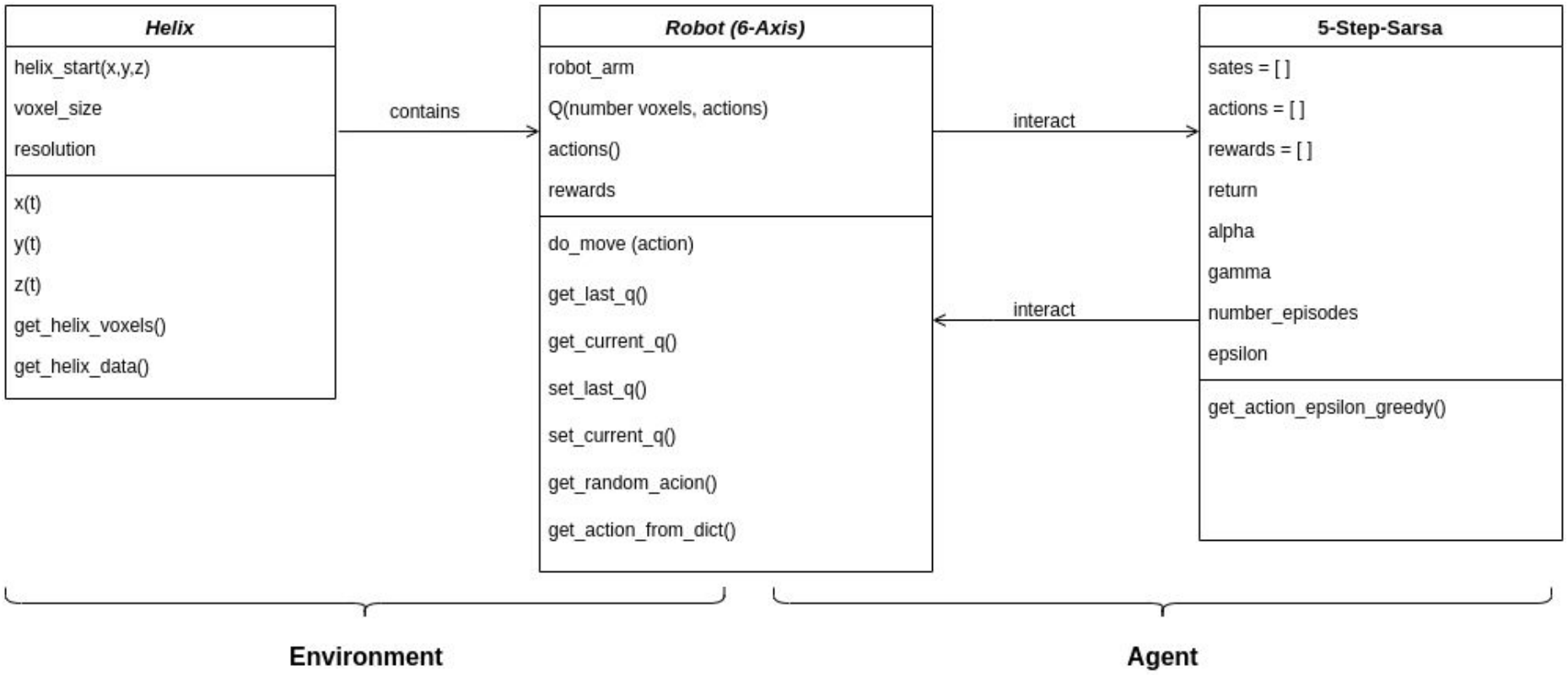
Validation

5-Step-Sarsa, race-track environment



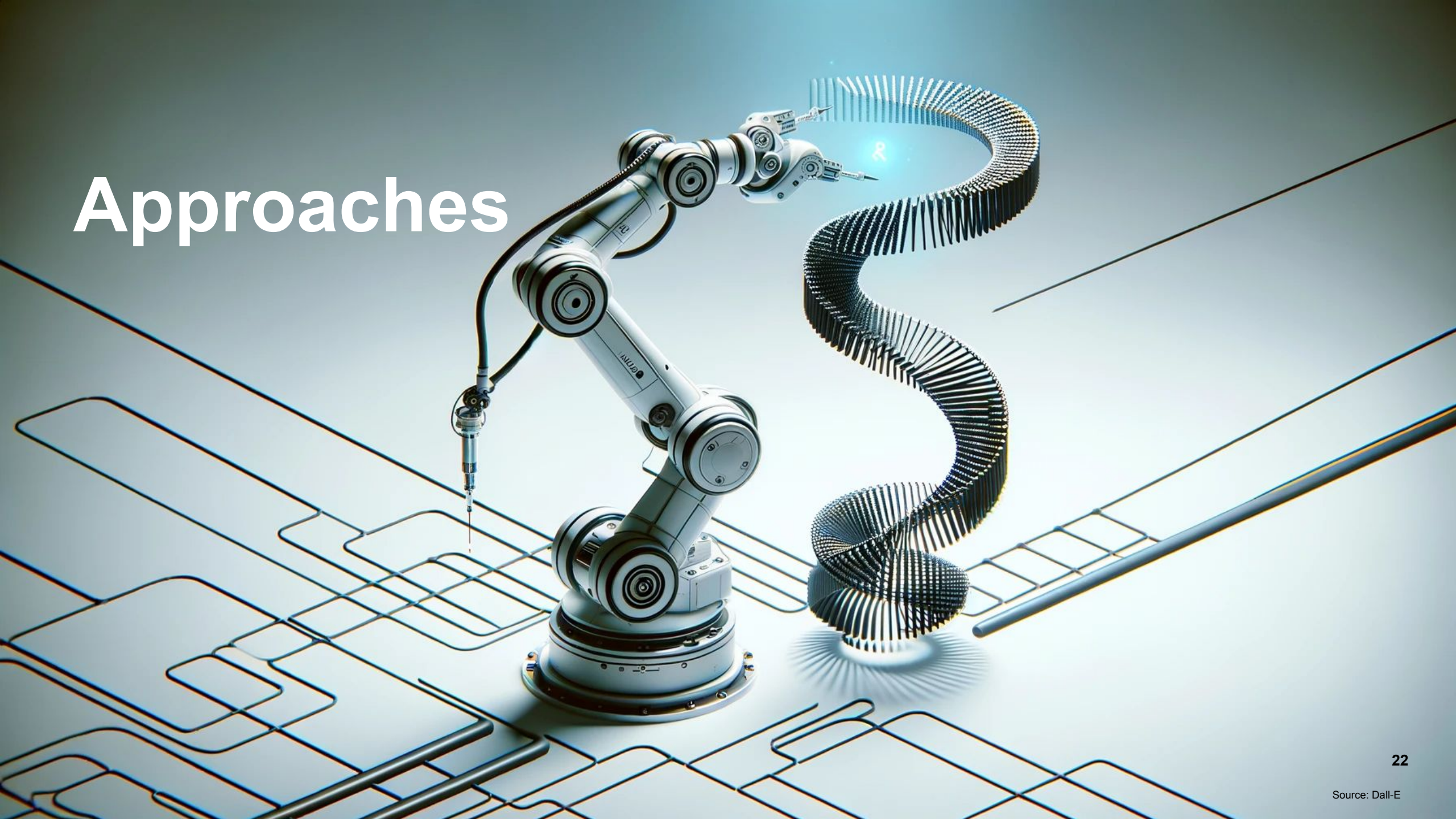
Implementation

Put all together, 6-Axis-Robot-Arm



* not all attributes and methods are shown

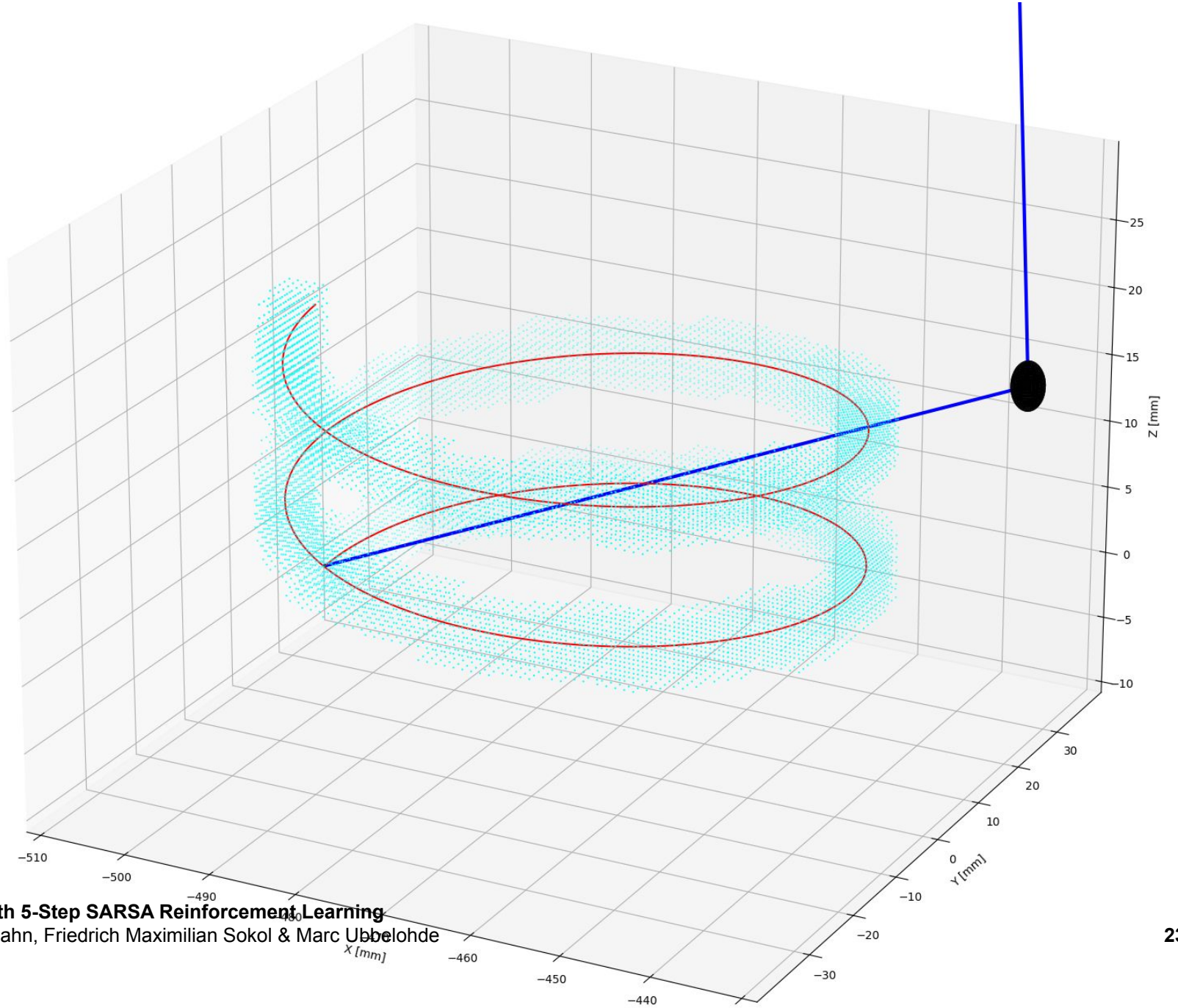
Approaches



Source: Dall-E

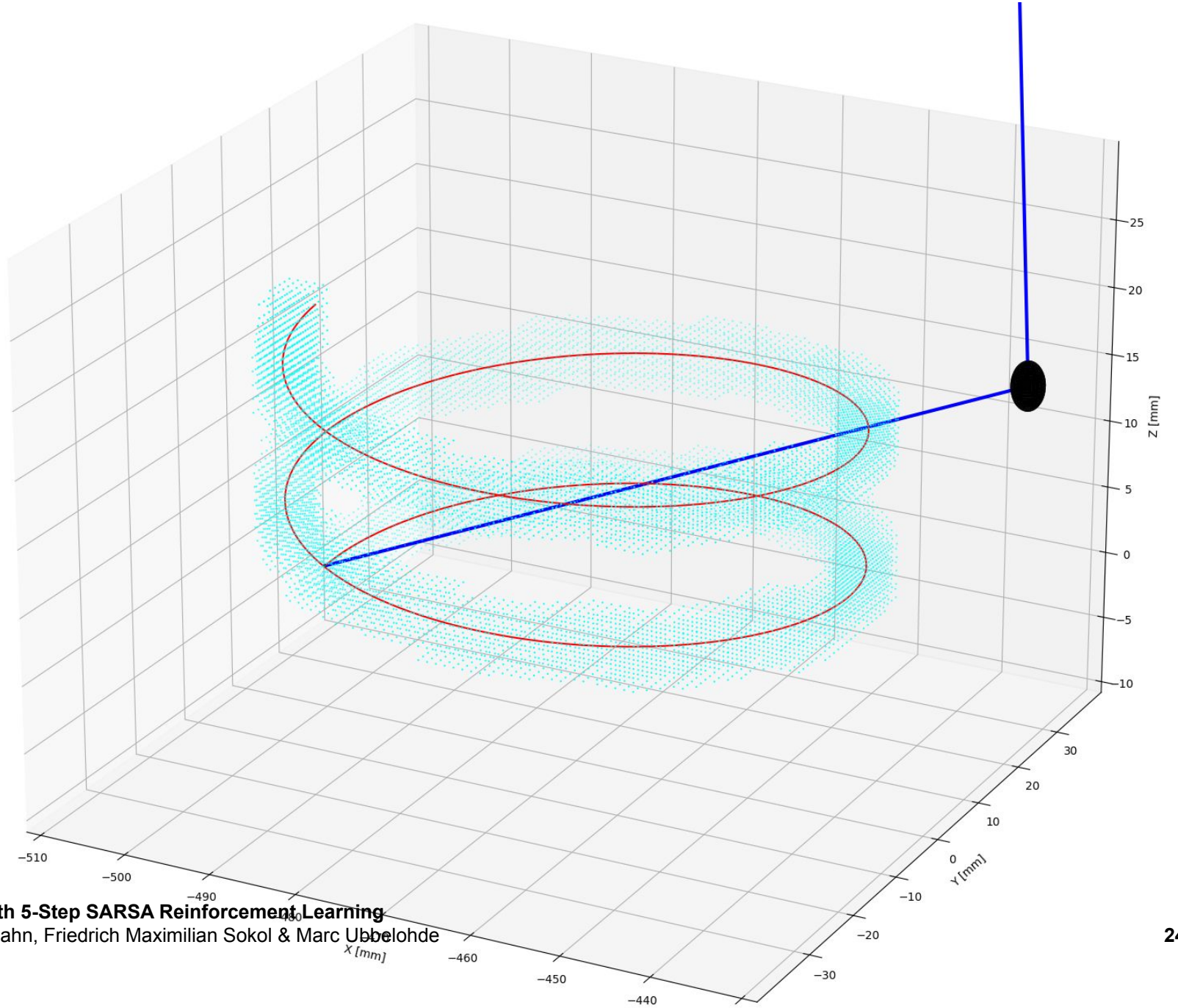
1st Approach

- Learn whole helix at once



1st Approach

- Learn whole helix at once
- Reward system:
  - -1 every step
  - 0 when in finishing voxels



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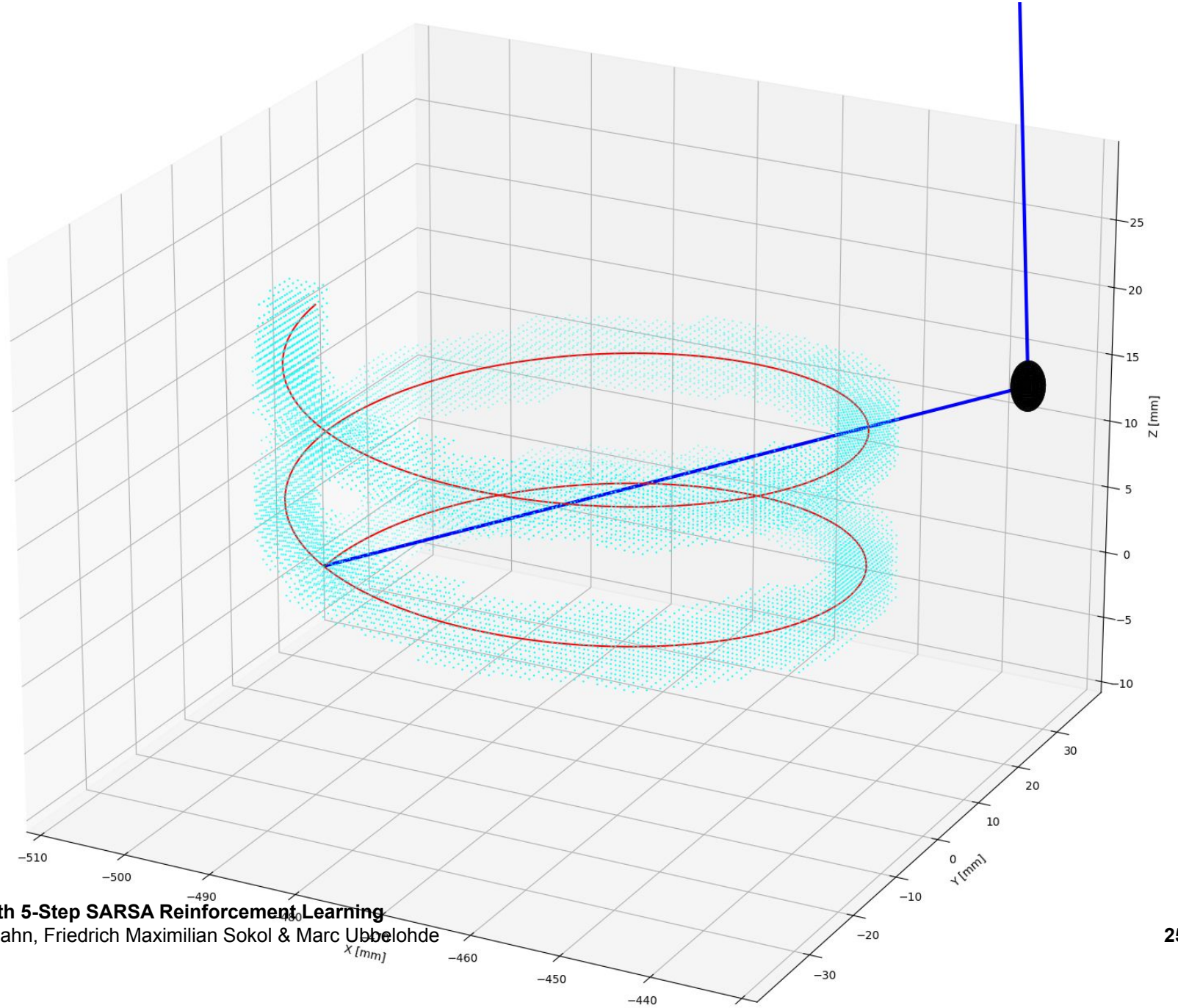

1st Approach

- Learn whole helix at once
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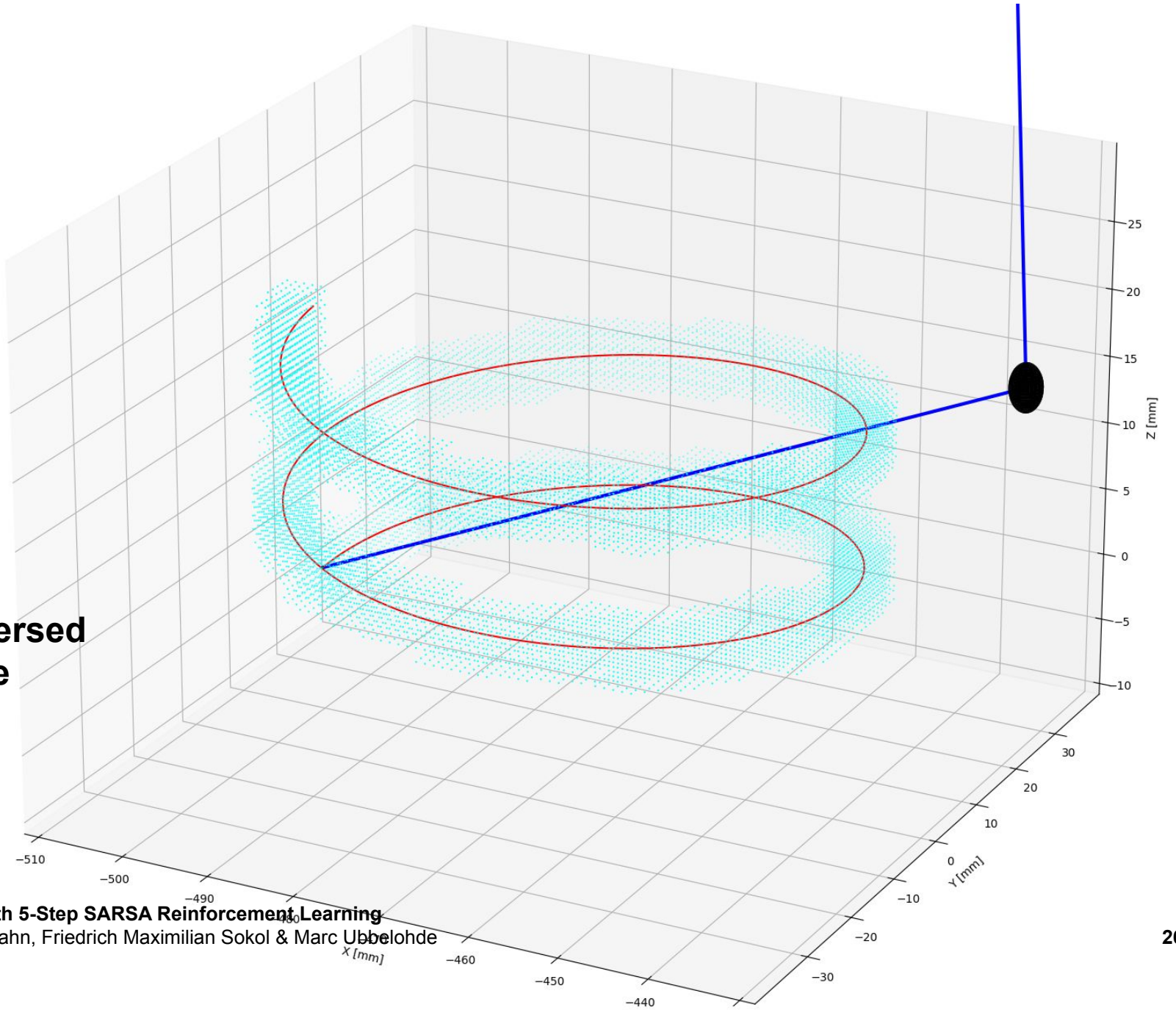
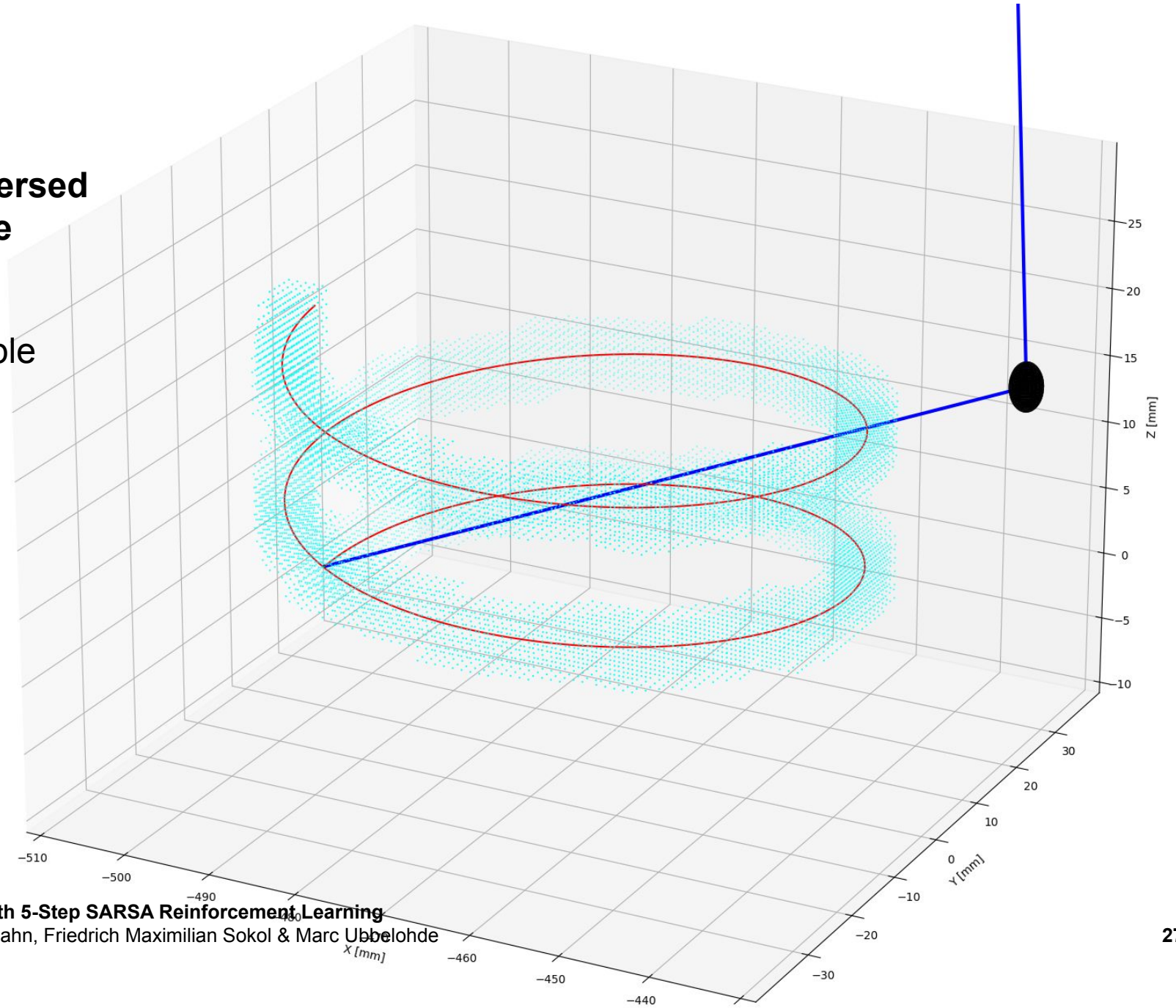
- **Problem: Helix needs to be traversed by pure chance at least one time**



1st Approach

- **Problem: Helix needs to be traversed by pure chance at least one time**

- Assumption: 100 out of 729 possible actions are good
- Probability to take good step: $\frac{100}{729}$



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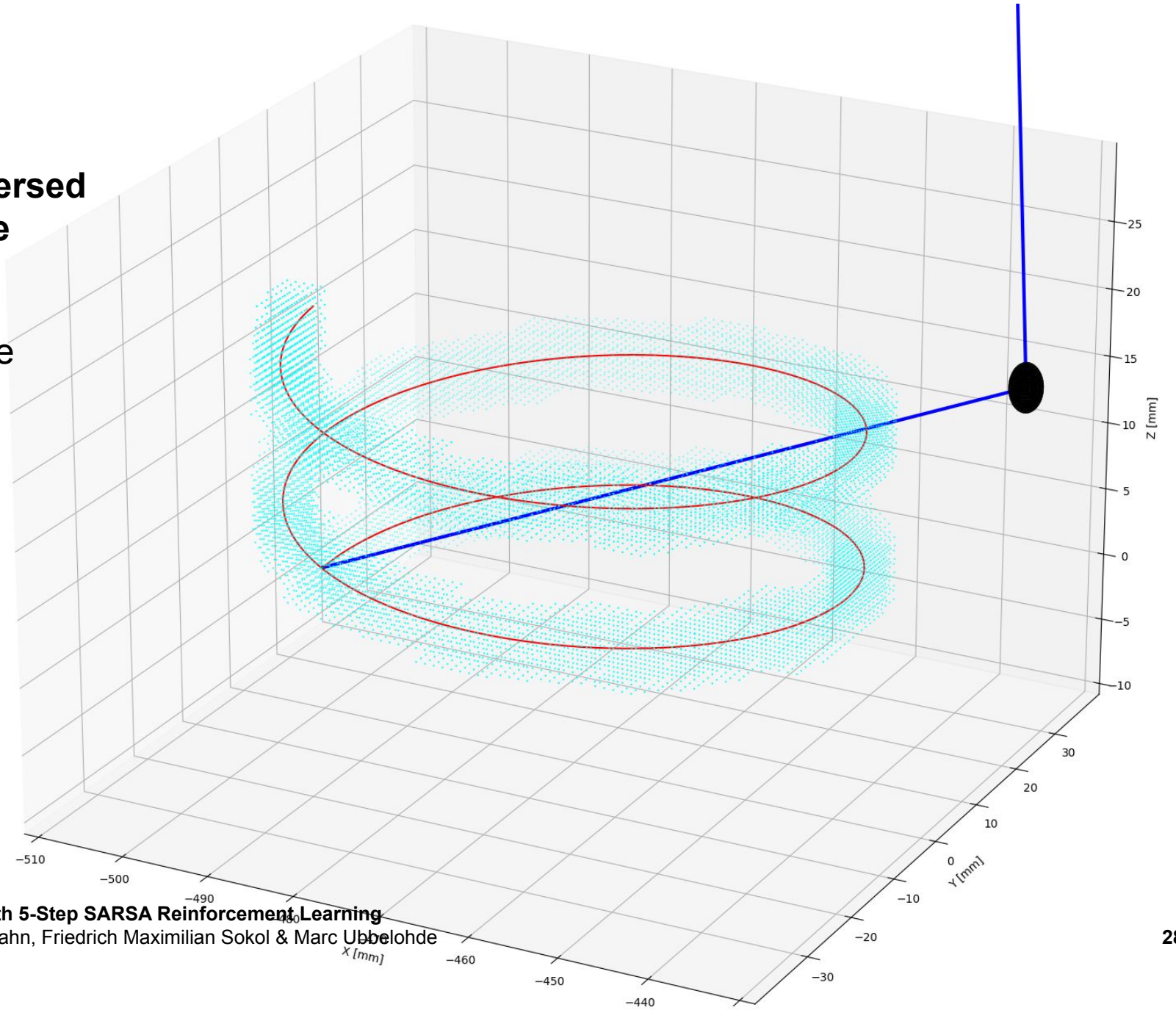

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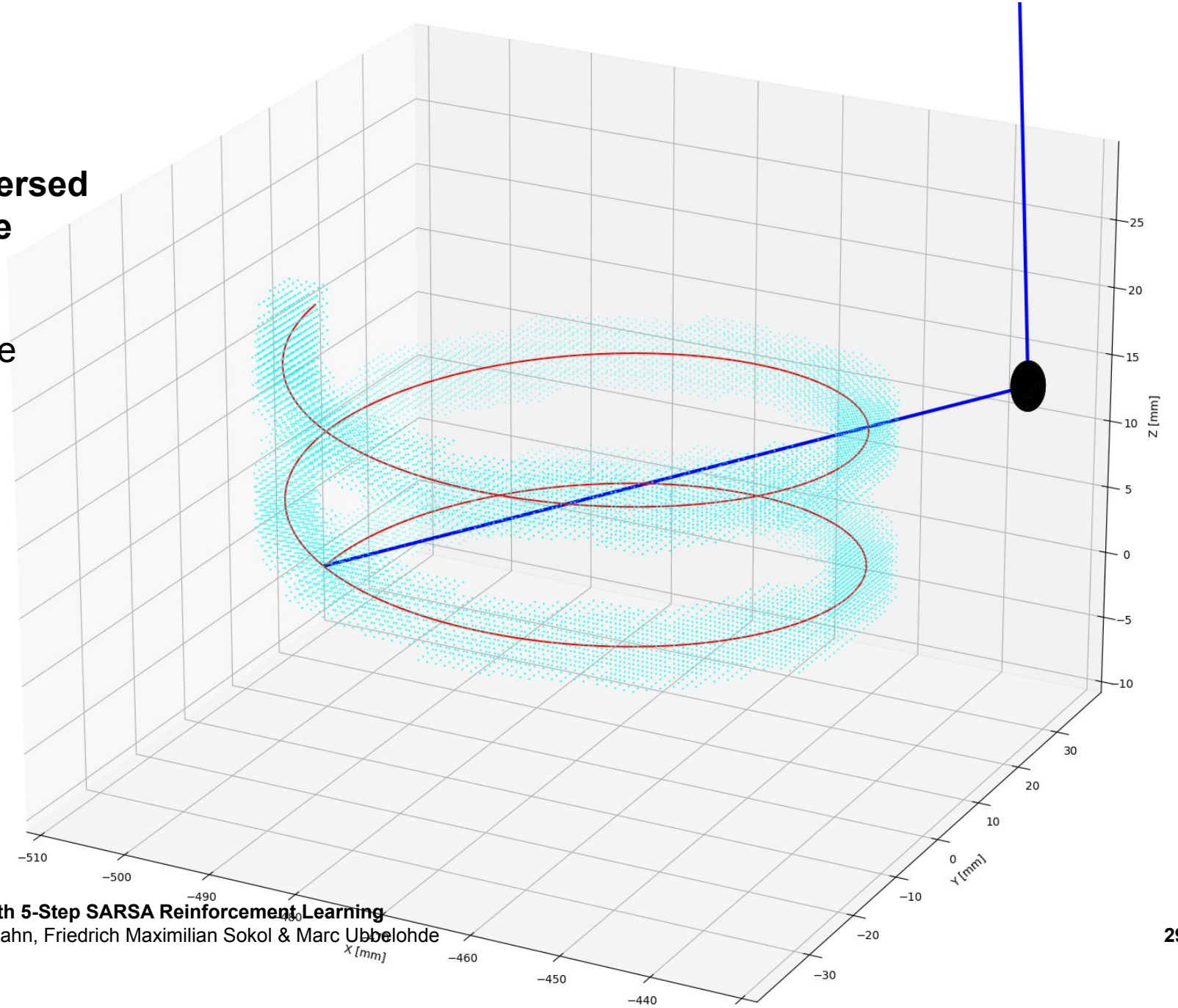
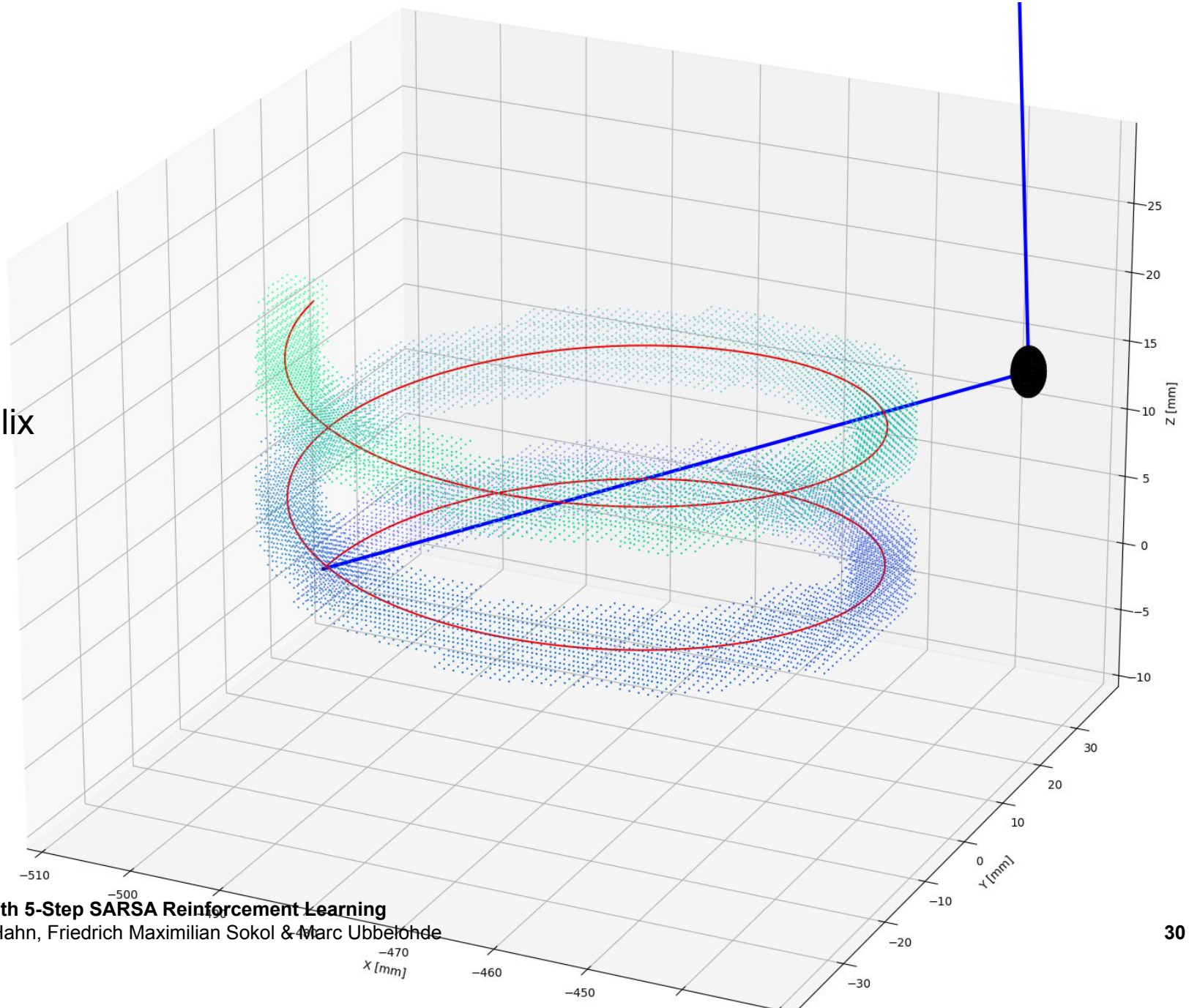
practically zero



2nd Approach

- Learn whole helix at once
- Revised reward system:
  - -5 when out of bounds
  - -1 for step at beginning of helix
  - increase reward linearly until helix is finished
  - 0 when in finishing voxels



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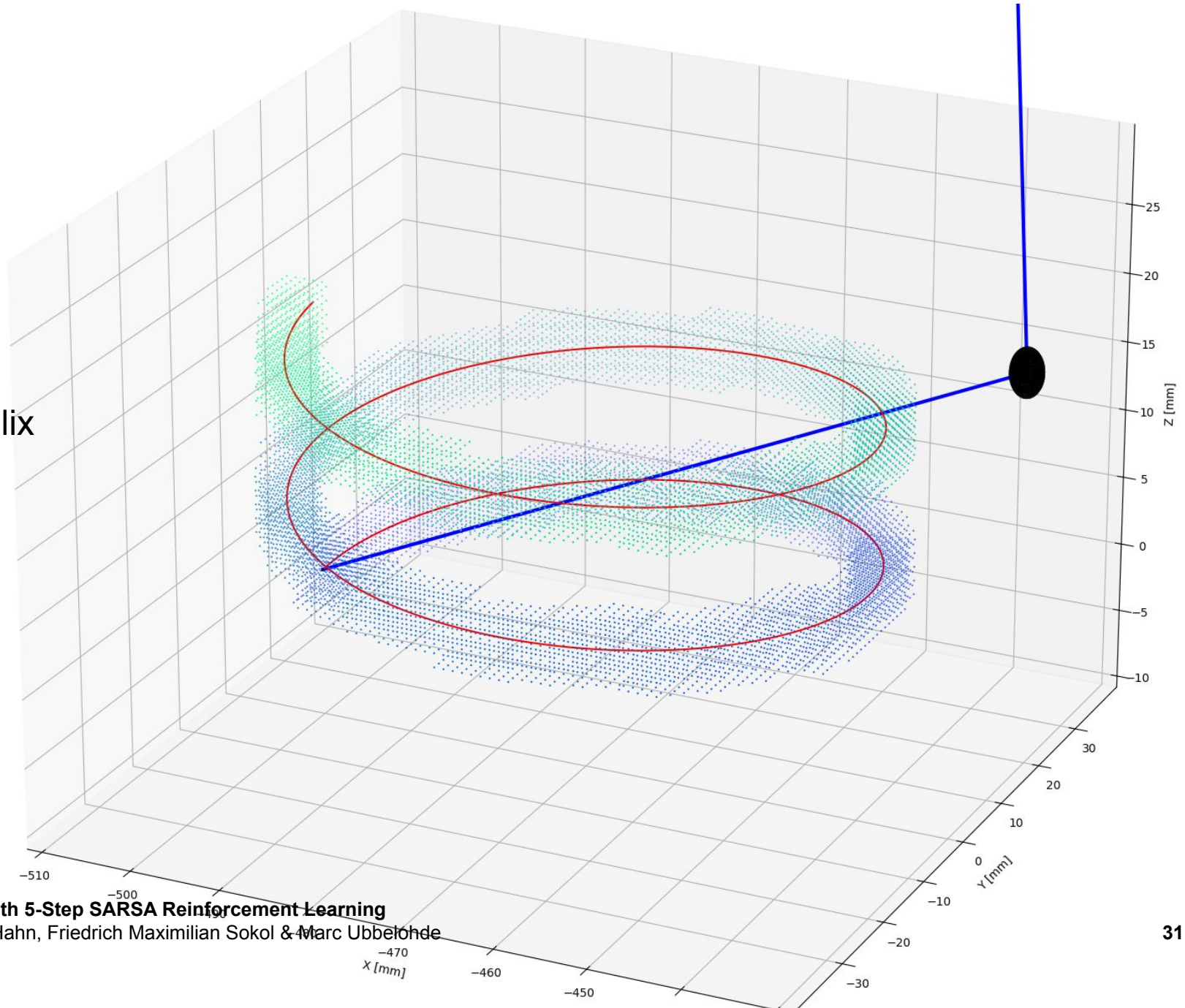

2nd Approach

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- Revised reward system:
  - -5 when out of bounds
  - -1 for step at beginning of helix
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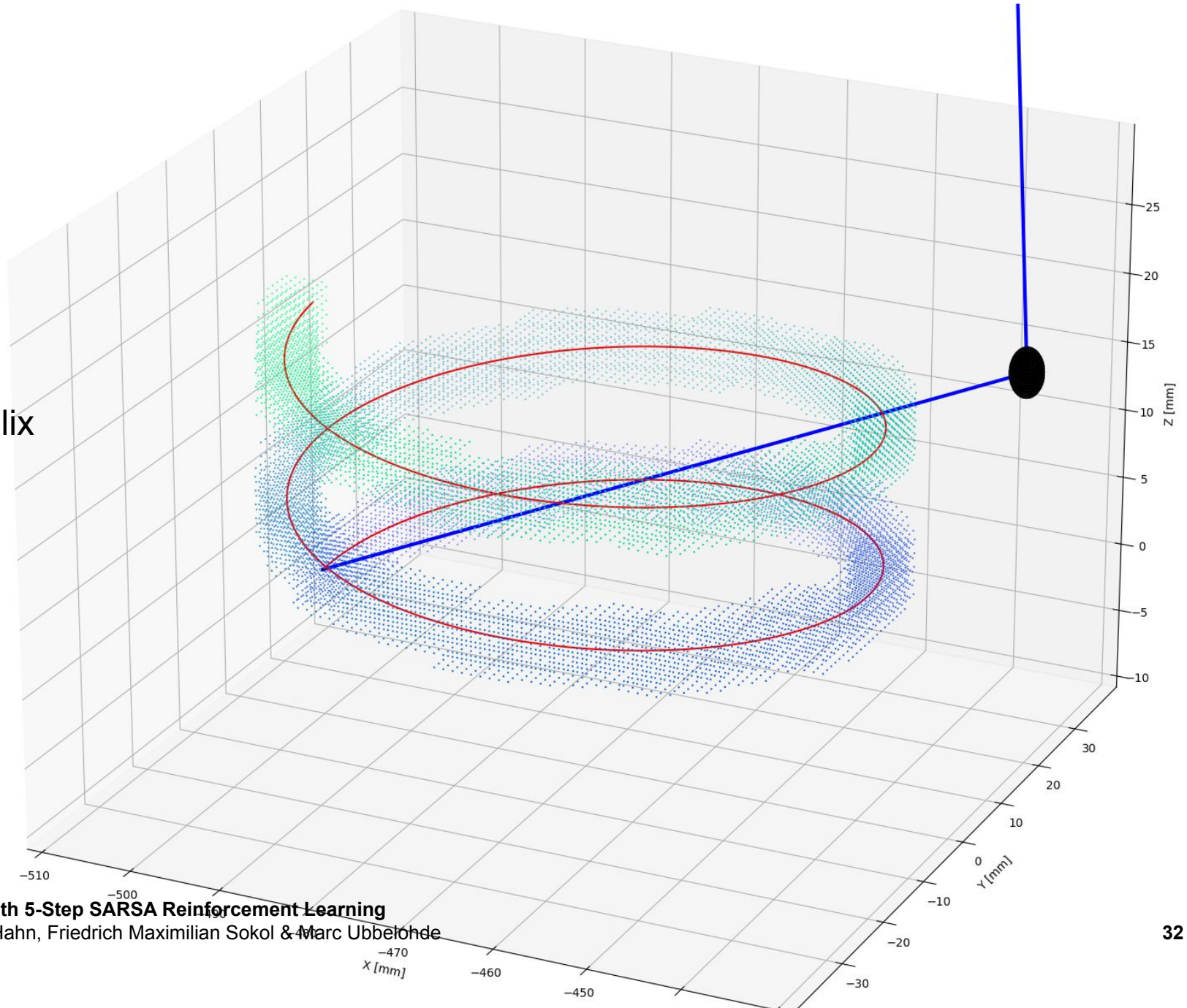
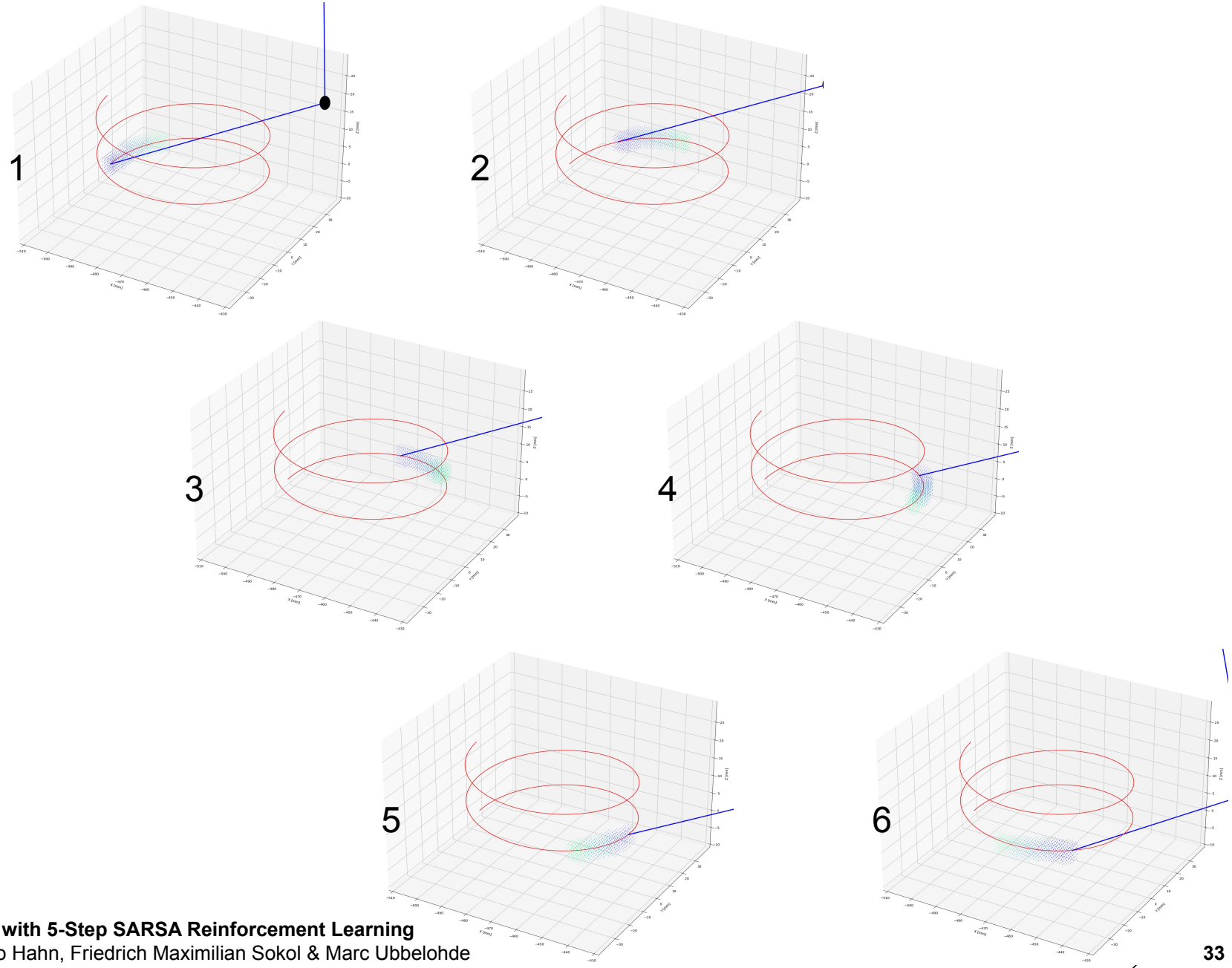
- … also never finished a single episode
- **But: it got further.**
- **Finished about 1/32 of the helix after 2 hours**



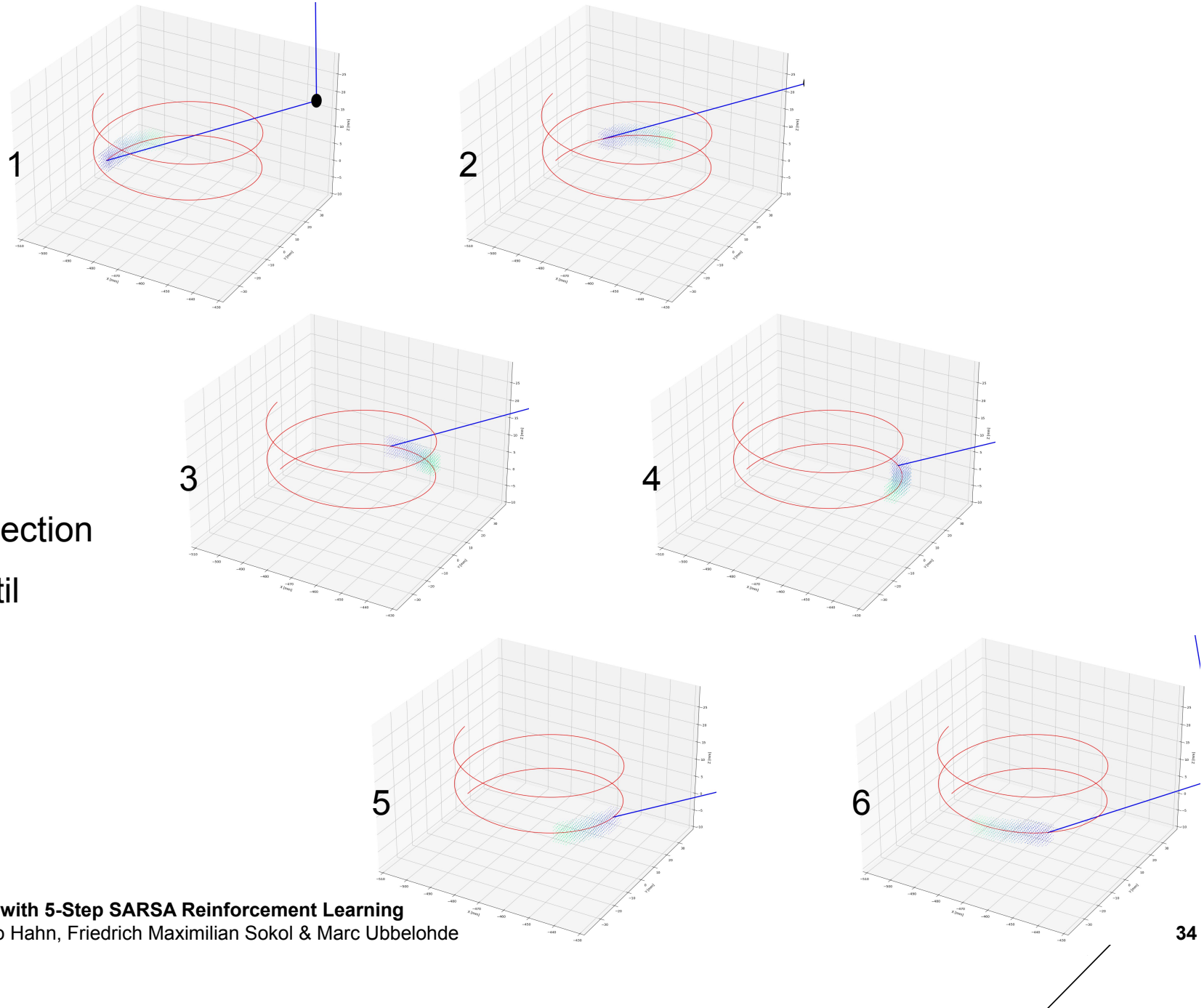
3rd Approach

- **Parallelization!**



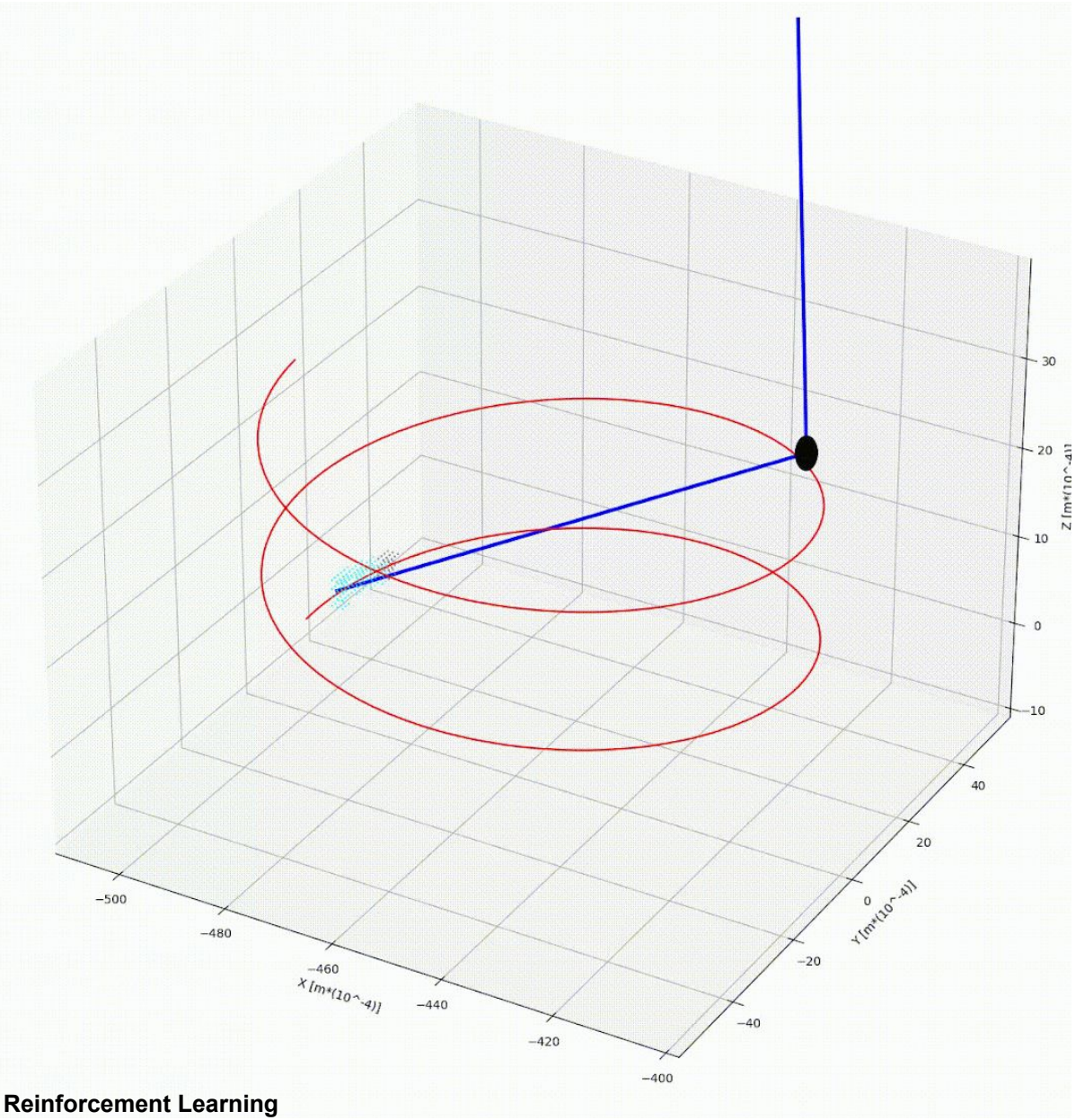
3rd Approach

- **Parallelization!**
- Split helix into sections
- Reward system:
  - -5 for going out of bounds
  - -1 for step at beginning of section
  - increase reward linearly until section is finished
  - 0 when in finishing voxels



3rd Approach

- **Parallelization!**
- Split helix into sections
- Reward system:
  - -5 for going out of bounds
  - -1 for step at beginning of section
  - increase reward linearly until section is finished
  - 0 when in finishing voxels
- **Sections are getting learned!**



3rd Approach

- **Parallelization!**
- What now?

```
                          Sections
          000  001  002  003  004  005  006  007
==================================================
Cycle   | 000  000  000  000  000  000  000  000
Episode| done 0299 0003 0019 0001 0000 0000 0000
```

```
max@Toaster: ~/Documents/Studium/WiSe2324/Reinforcement_Learning/rl_team_03/code 91x26

  0[||||||      28.6%]   3[||||||||||79.9%]   6[||||||||||68.3%]   9[||||||||||100.0%]
  1[||||||||||88.5%]   4[||||||||||100.0%]   7[||||||||    44.7%]  10[||||||||    44.1%]
  2[||||||||    43.4%]   5[||||||||||100.0%]   8[||||||||||100.0%]  11[||||||||||77.4%]
Mem[||||||||||||||||||||||||||6.39G/13.3G] Tasks: 176, 1209 thr, 207 kthr; 9 running
Swp[                            0K/4.00G] Load average: 6.43 2.92 1.43
                                          Uptime: 08:46:37

 Main  I/O
   PID USER      PRI  NI  VIRT   RES   SHR S CPU%▽MEM%   TIME+  Command
 30170 max      20   0  575M 62848 21376 R 102.1  0.4  0:50.14 python3 reinforce.py
 30184 max      20   0  577M 52604  9616 R 101.7  0.4  0:50.33 python3 reinforce.py
 30186 max      20   0  577M 52744  9616 R 101.7  0.4  0:49.86 python3 reinforce.py
 30201 max      20   0  577M 52616  9616 R 101.7  0.4  0:49.26 python3 reinforce.py
 30204 max      20   0  577M 52620  9616 R 101.7  0.4  0:49.03 python3 reinforce.py
 30185 max      20   0  577M 52604  9616 R 101.3  0.4  0:50.04 python3 reinforce.py
 30188 max      20   0  577M 52744  9744 R 101.3  0.4  0:49.66 python3 reinforce.py
 30189 max      20   0  577M 52360  9488 R 101.3  0.4  0:49.45 python3 reinforce.py
```

3rd Approach

- **Parallelization!**
- What now?
- Stitch sections together to receive the full policy
- Finish training based on the stitched Q values

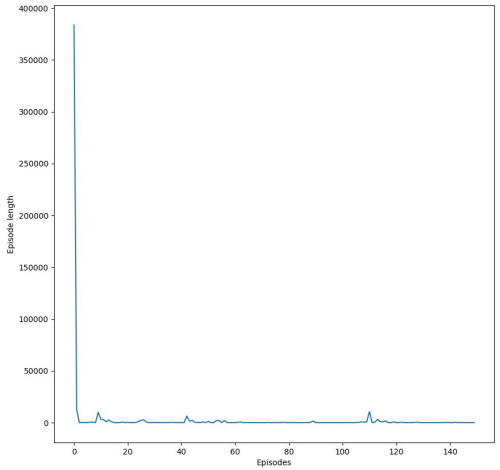
```
                          Sections
          000   001   002   003   004   005   006   007
=================================================
Cycle   | 000   000   000   000   000   000   000   000
Episode| done 0299 0003 0019 0001 0000 0000 0000
```

```
max@Toaster: ~/Documents/Studium/WiSe2324/Reinforcement_Learning/rl_team_03/code 91x26

  0[||||||      28.6%]   3[||||||||||79.9%]   6[||||||||||68.3%]   9[||||||||||100.0%]
  1[||||||||||88.5%]   4[||||||||||100.0%]   7[||||||||    44.7%]  10[||||||||    44.1%]
  2[||||||||    43.4%]   5[||||||||||100.0%]   8[||||||||||100.0%]  11[||||||||||77.4%]
Mem[||||||||||||||||||||||||||6.39G/13.3G] Tasks: 176, 1209 thr, 207 kthr; 9 running
Swp[                            0K/4.00G] Load average: 6.43 2.92 1.43
                                          Uptime: 08:46:37

 Main   I/O
   PID USER      PRI  NI  VIRT   RES   SHR S CPU%▽MEM%   TIME+  Command
 30170 max      20   0  575M 62848 21376 R 102.1  0.4  0:50.14 python3 reinforce.py
 30184 max      20   0  577M 52604  9616 R 101.7  0.4  0:50.33 python3 reinforce.py
 30186 max      20   0  577M 52744  9616 R 101.7  0.4  0:49.86 python3 reinforce.py
 30201 max      20   0  577M 52616  9616 R 101.7  0.4  0:49.26 python3 reinforce.py
 30204 max      20   0  577M 52620  9616 R 101.7  0.4  0:49.03 python3 reinforce.py
 30185 max      20   0  577M 52604  9616 R 101.3  0.4  0:50.04 python3 reinforce.py
 30188 max      20   0  577M 52744  9744 R 101.3  0.4  0:49.66 python3 reinforce.py
 30189 max      20   0  577M 52360  9488 R 101.3  0.4  0:49.45 python3 reinforce.py
```

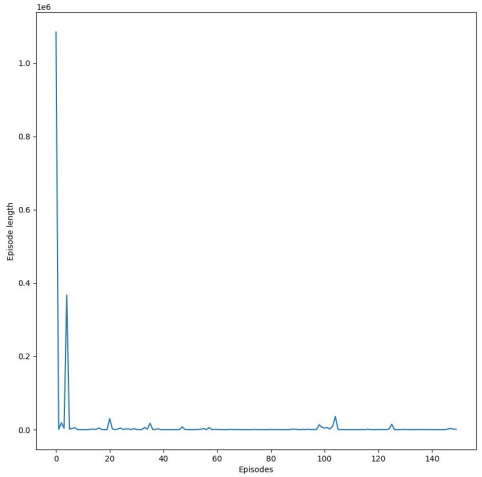
3rd Approach

- **Parallelization!**

Section 1



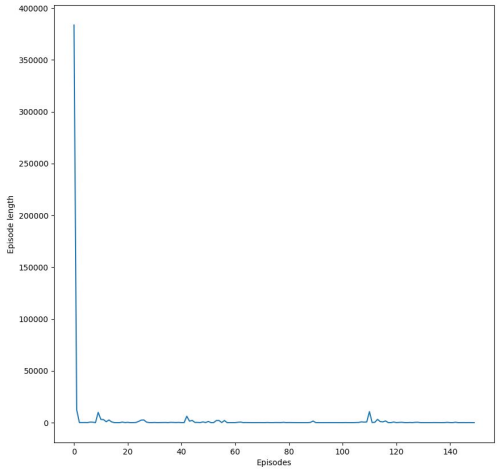
Section 2



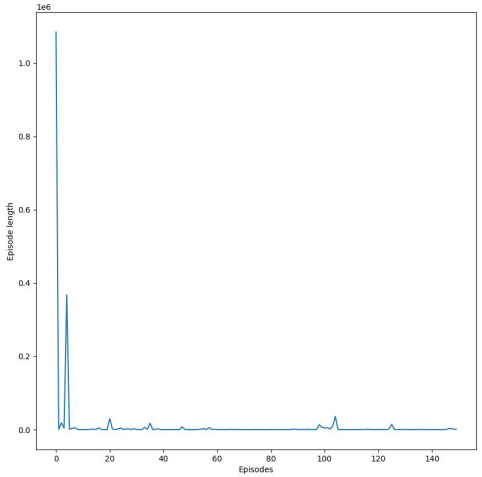
3rd Approach

- **Parallelization!**
- After stitching sections together:
  - good start in episode lengths
  - episode length increases with training time

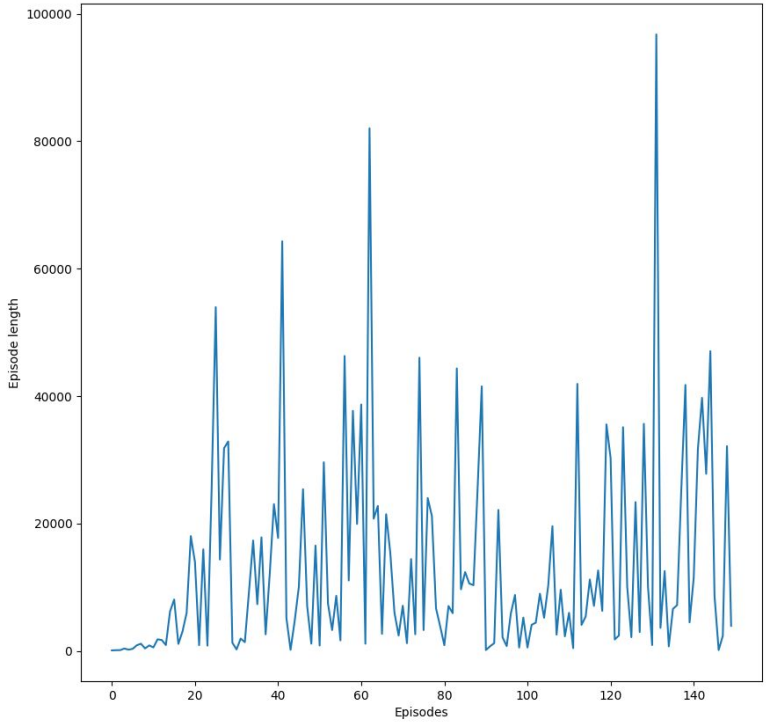
Section 1



Section 2



Section 1 + 2



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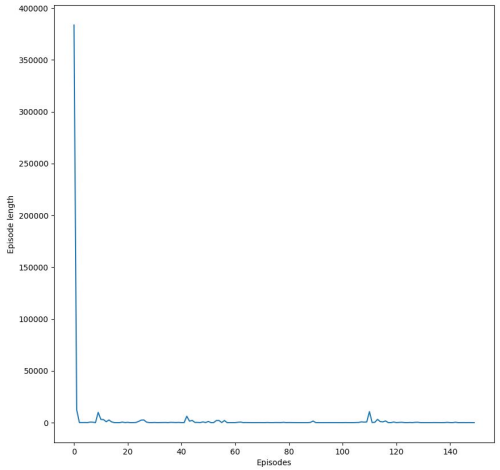
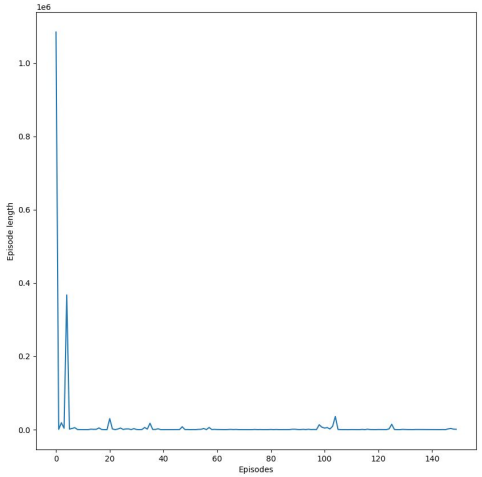
WHY?

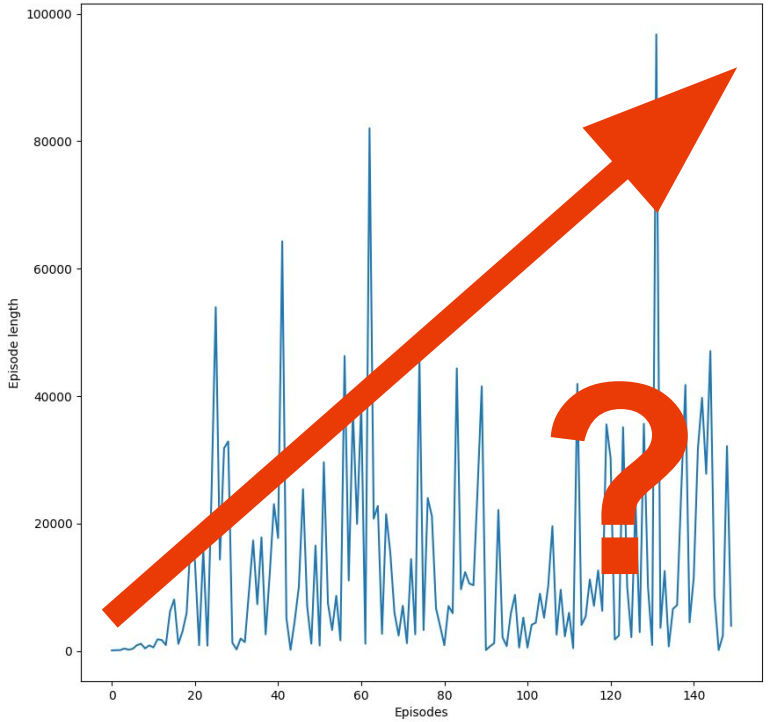
Section 1



Section 2

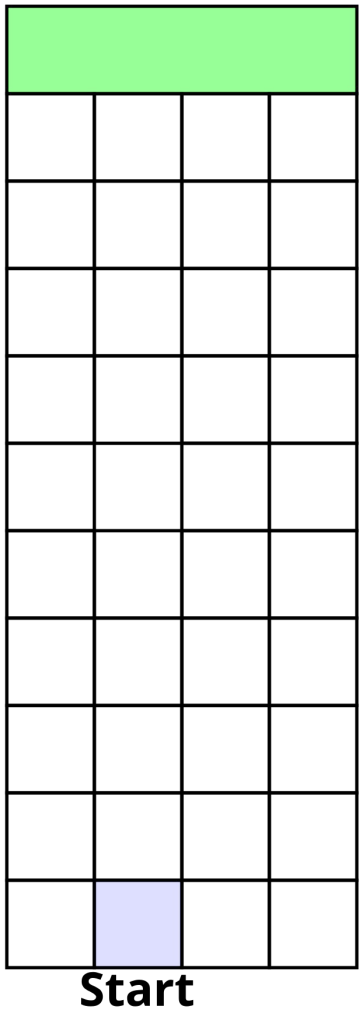


Section 1 + 2



3rd Approach

- **Let' simplify…**
- Environment:
  - Gridworld
  - Possible Moves:
    - North, South, East, West
- Reward System:
  - -1 every step
  - 0 when in winning pixels



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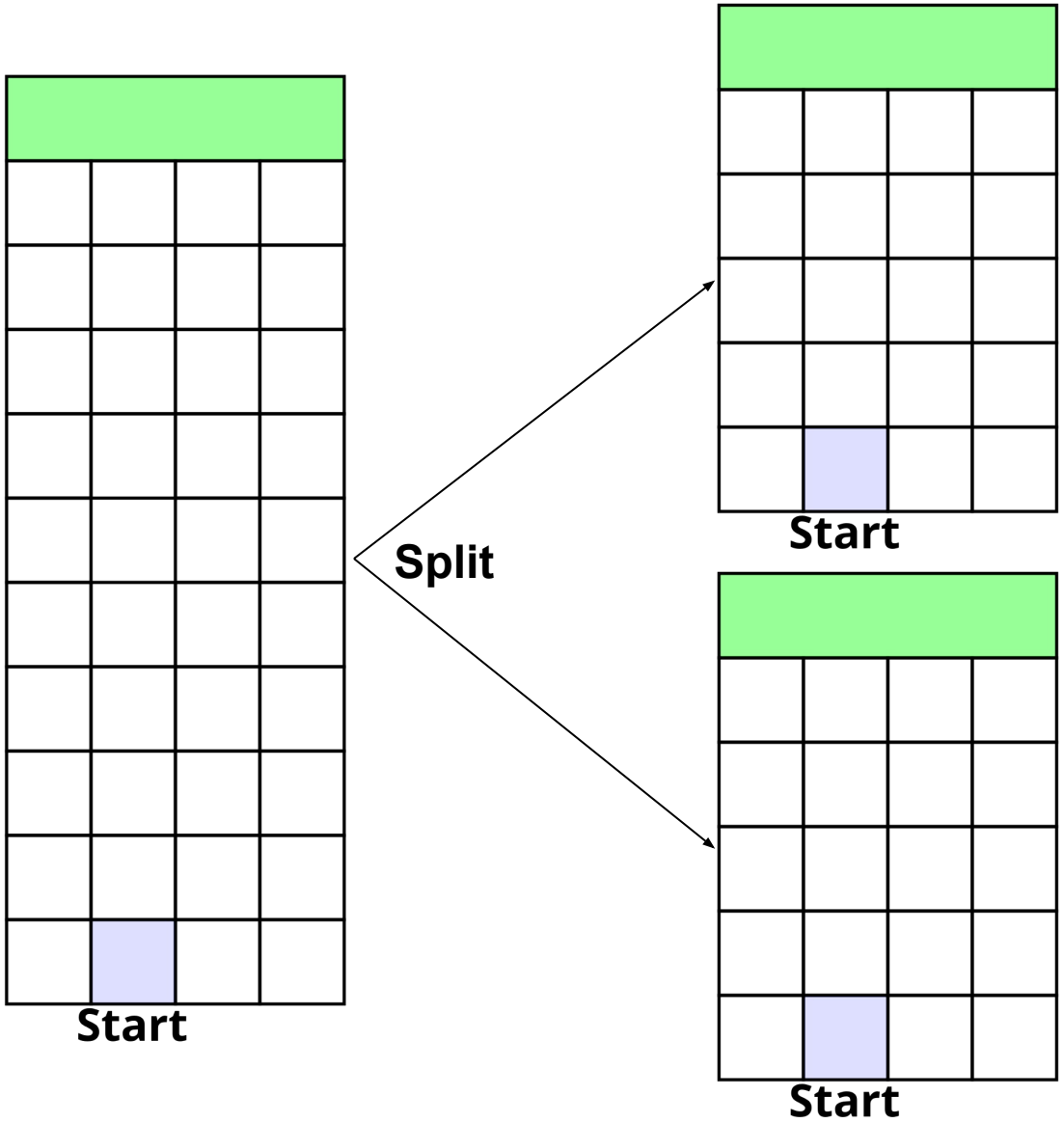
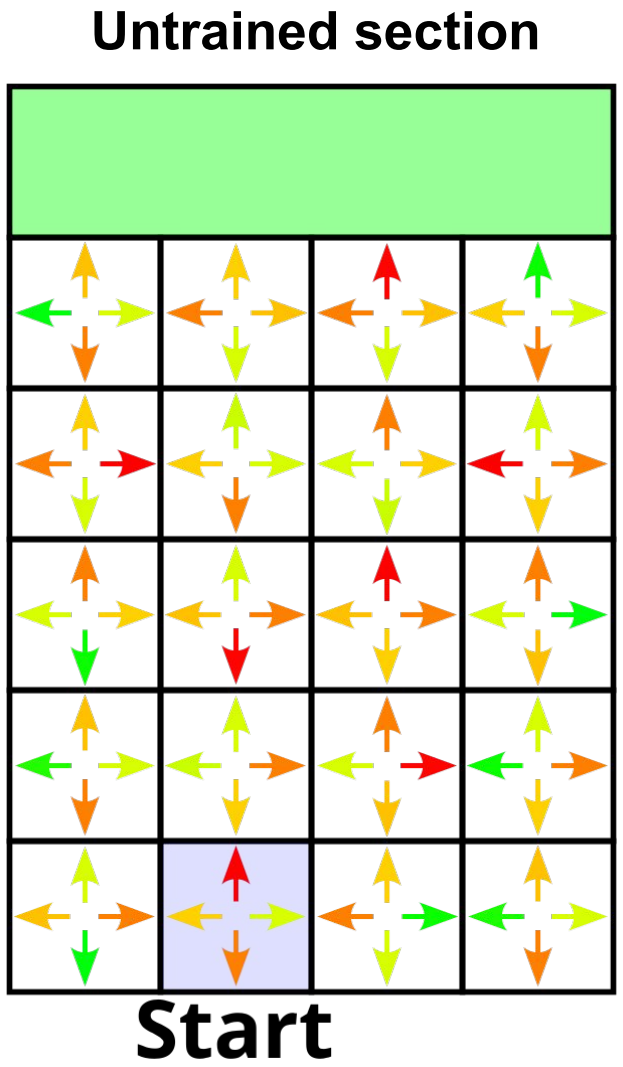


3rd Approach

- Green arrow = high Q value
- Red arrow = low Q value



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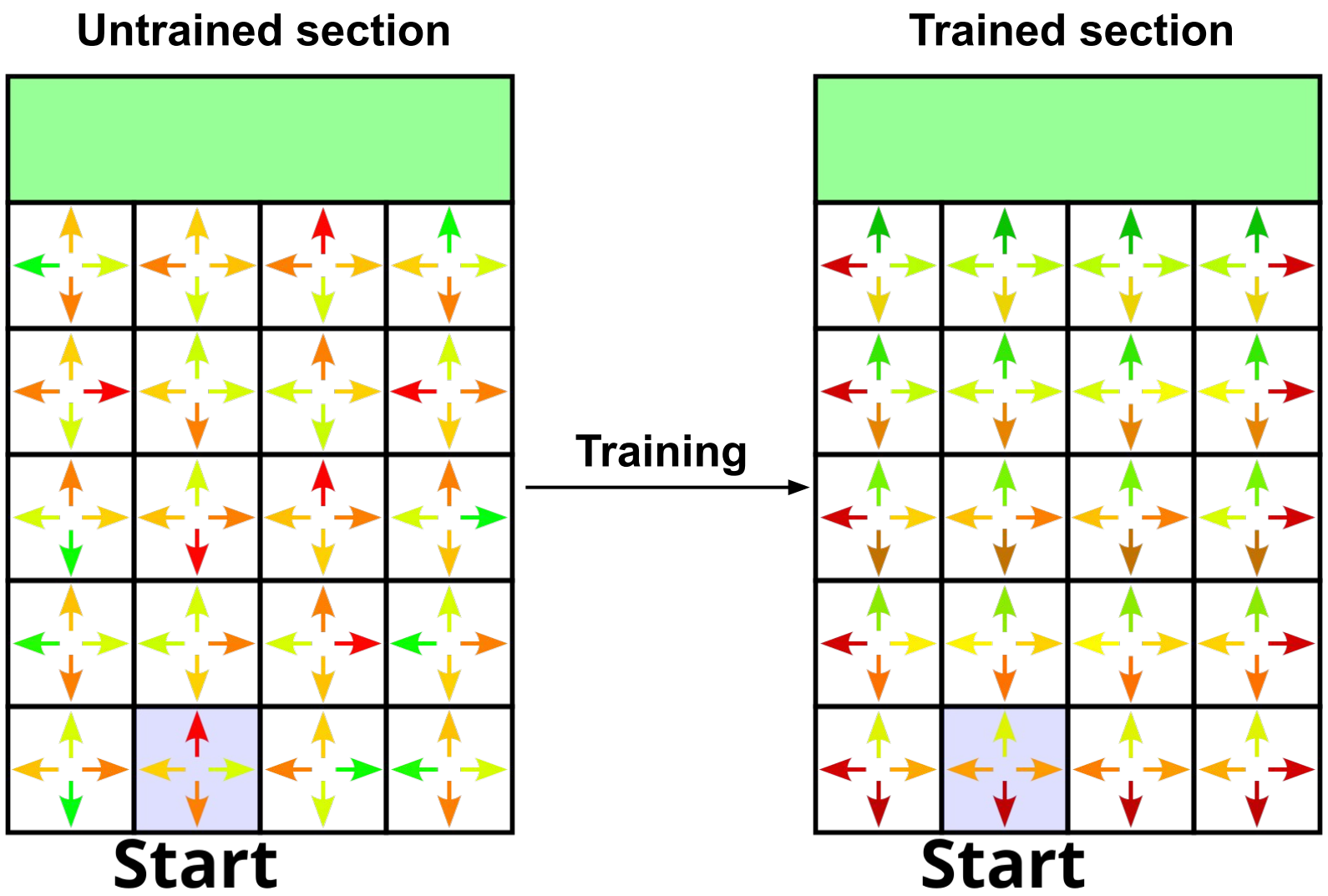
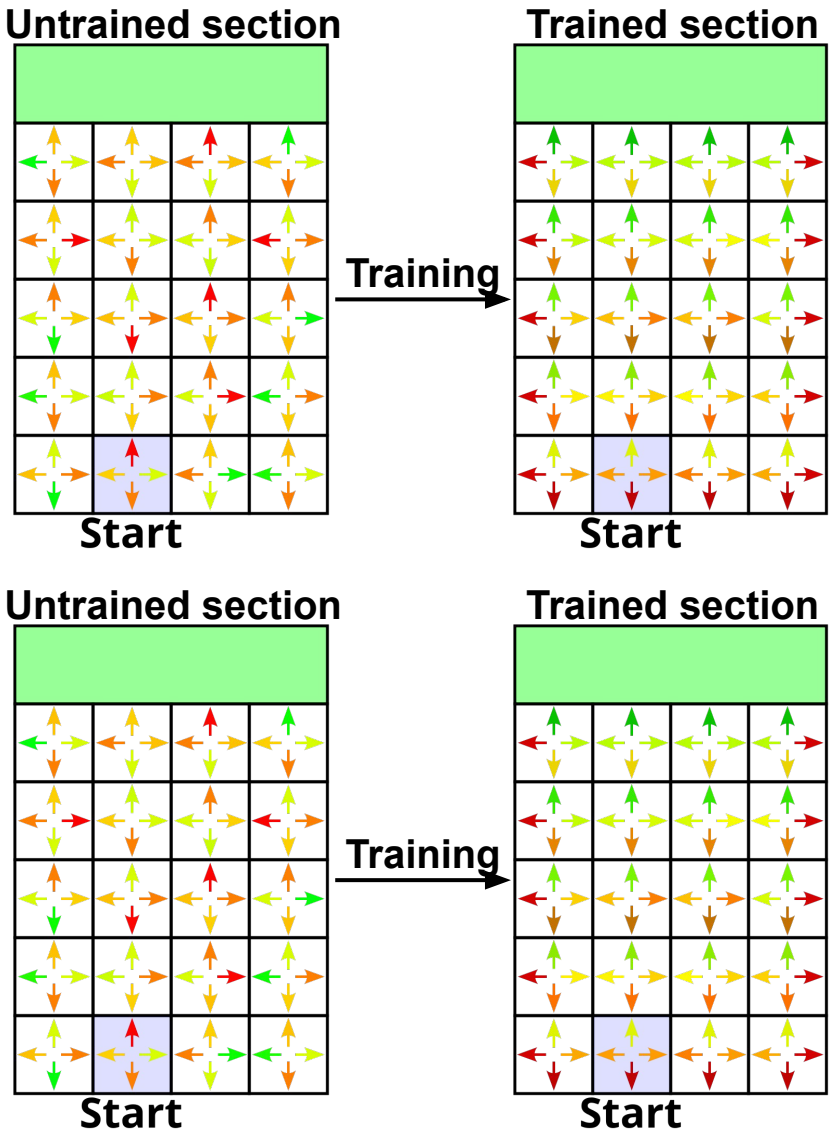
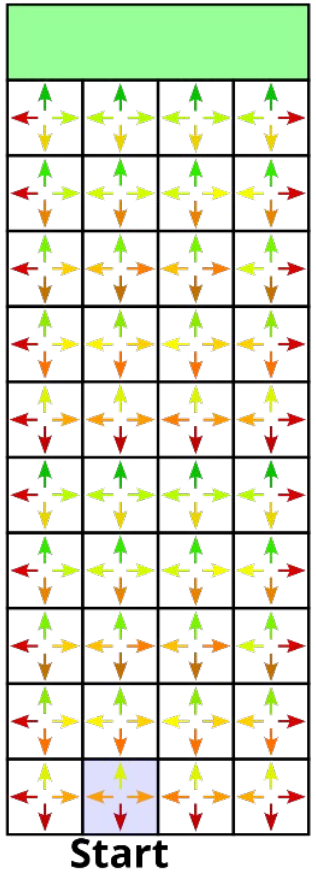


3rd Approach

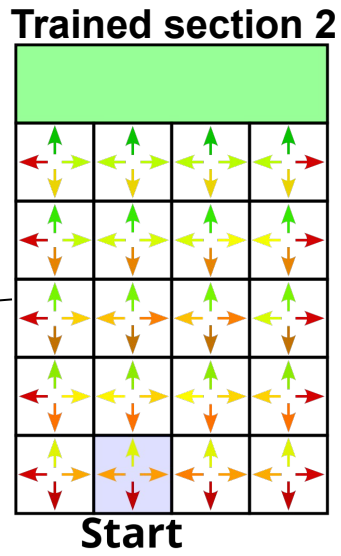
- Green arrow = high Q value
- Red arrow = low Q value
- **Train both sections!**

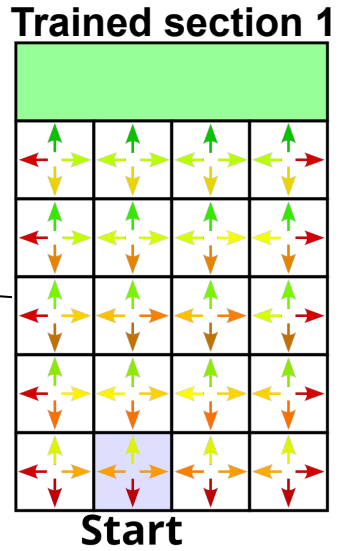


3rd Approach

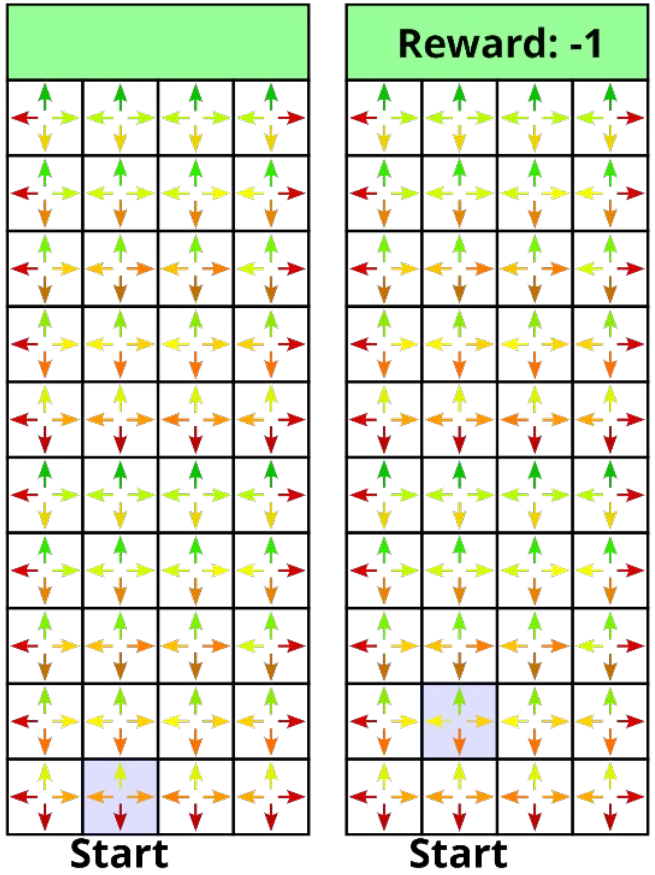


- … stitch sections together and train even more

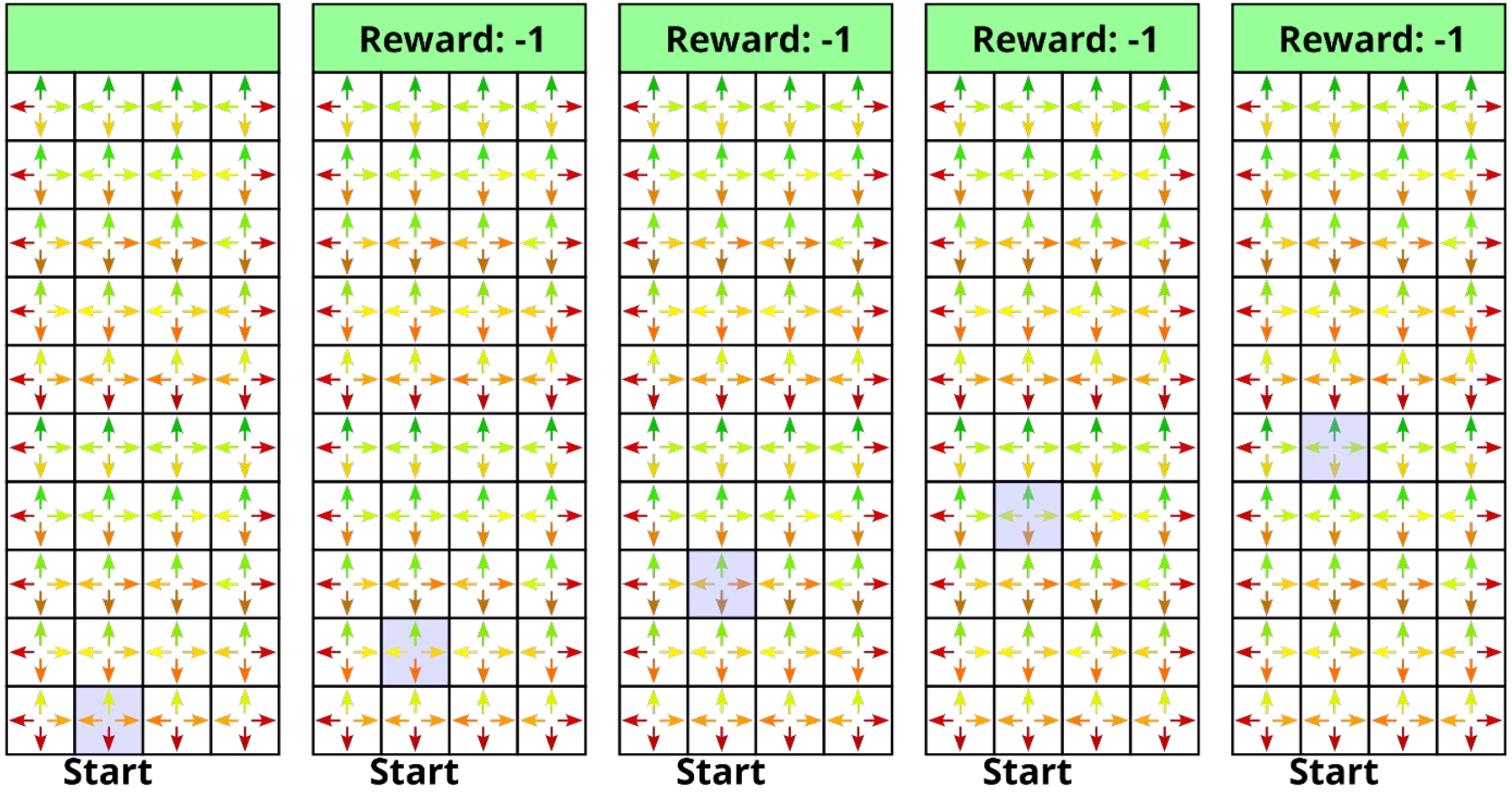




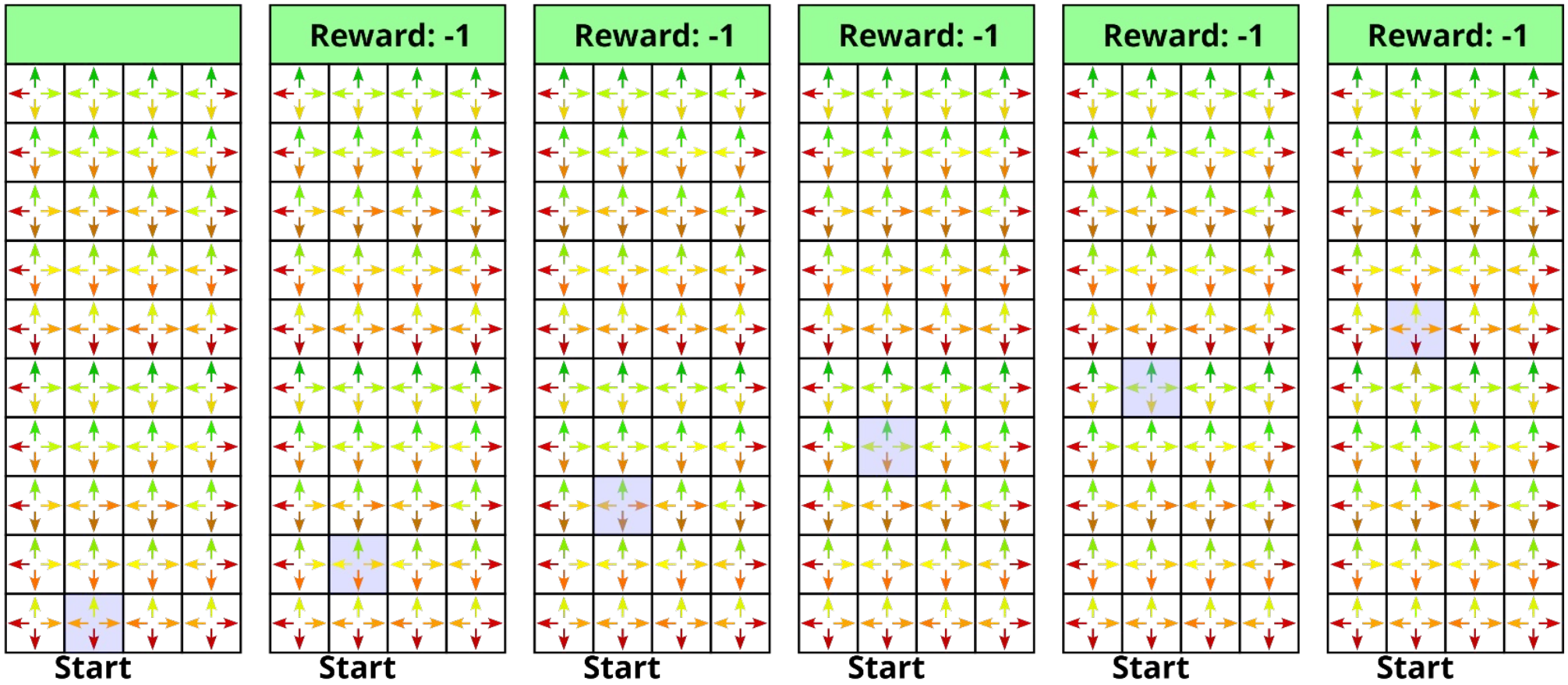
3rd Approach



3rd Approach

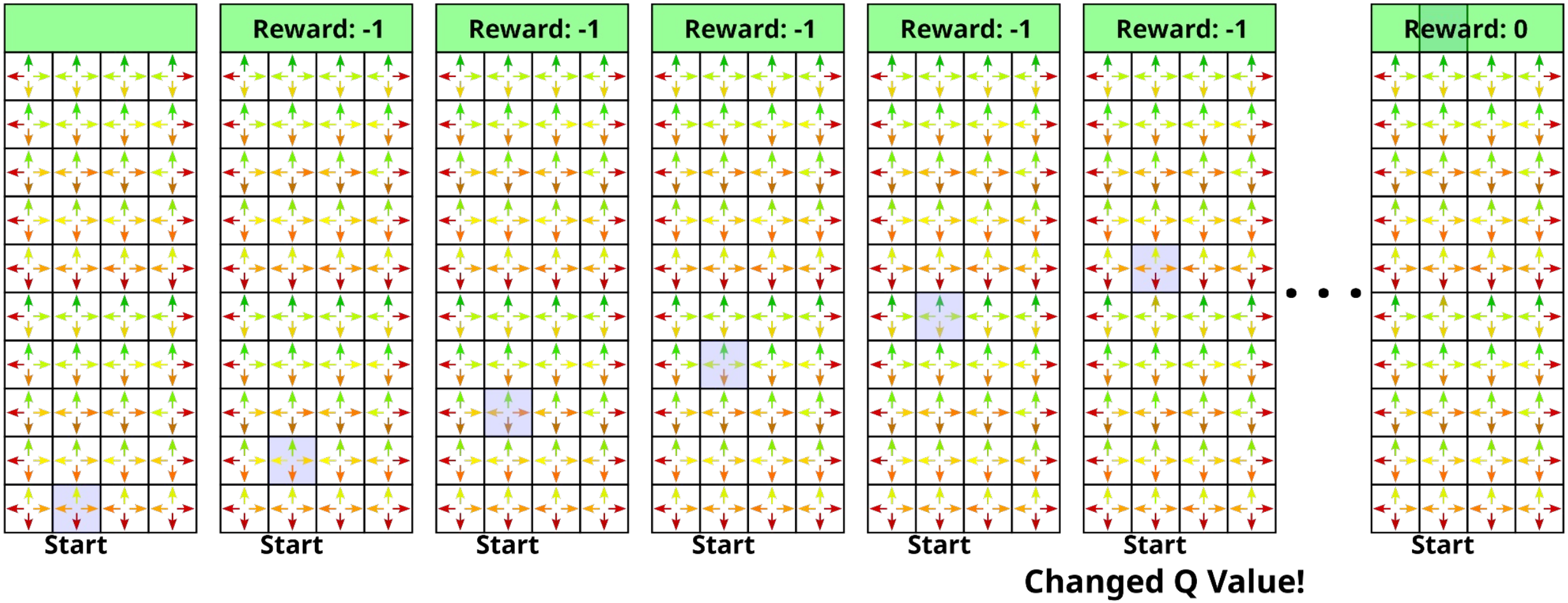


3rd Approach

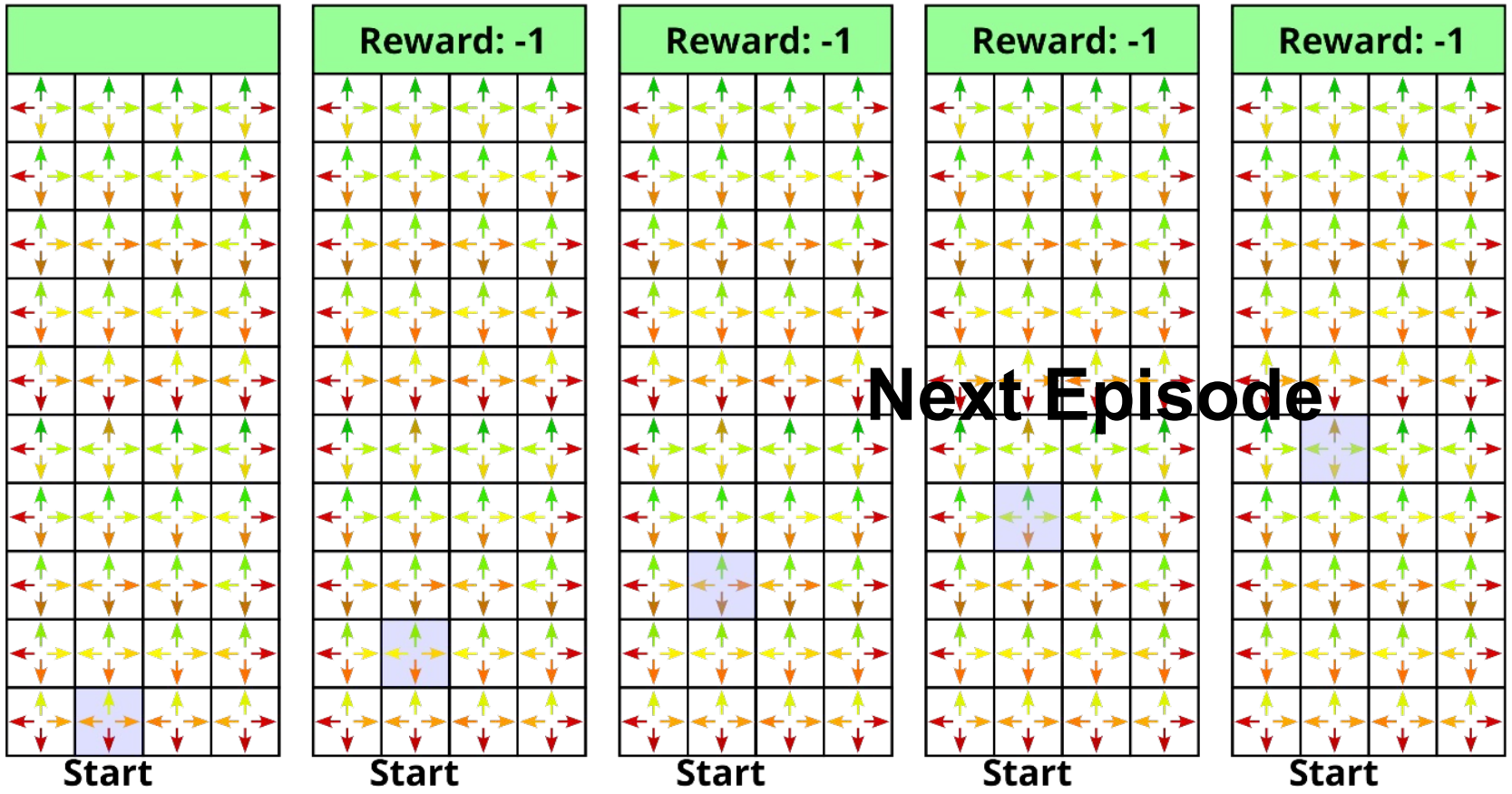


We get penalized where we didn't get penalized before!

3rd Approach



3rd Approach



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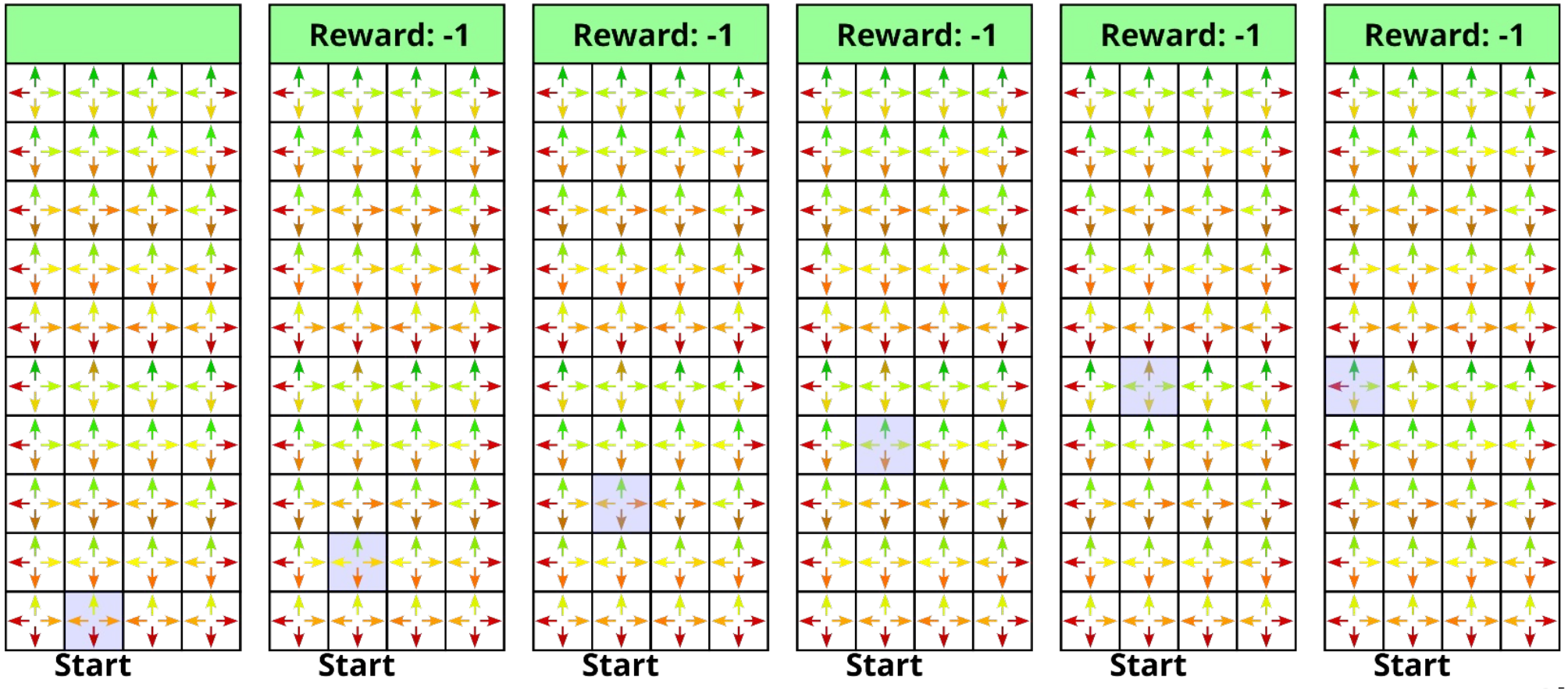

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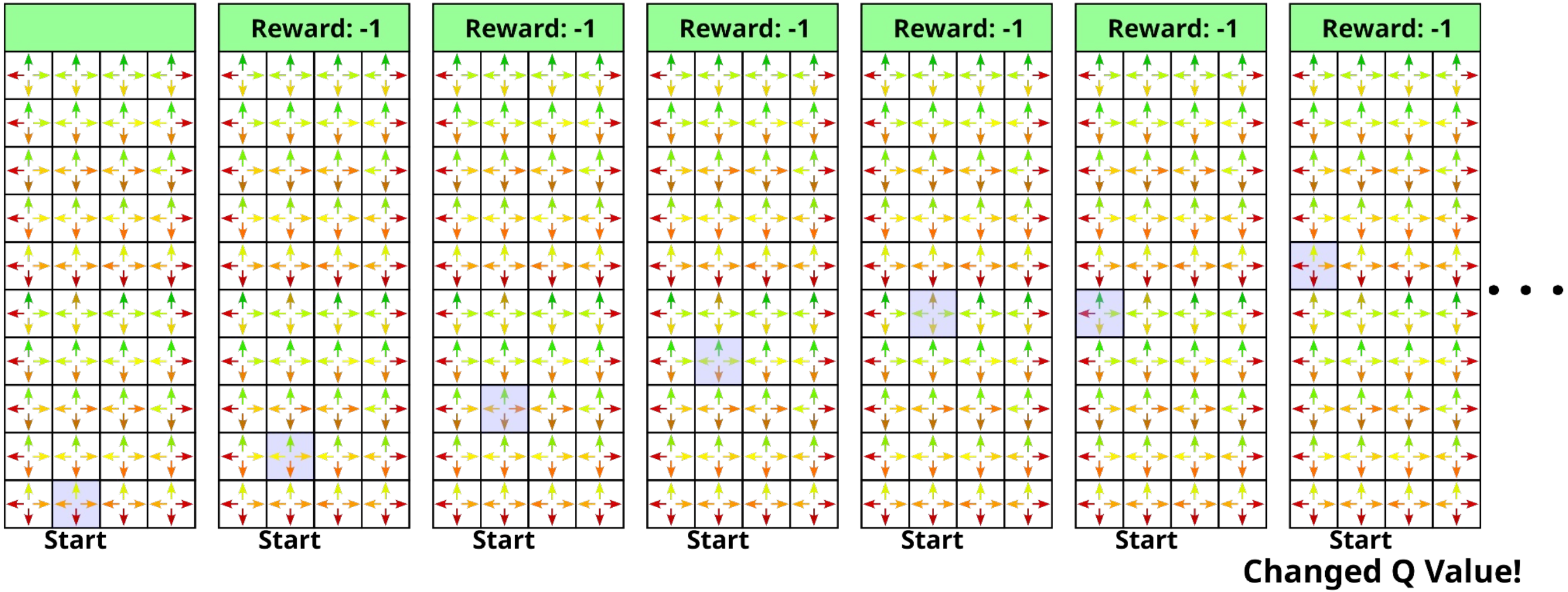

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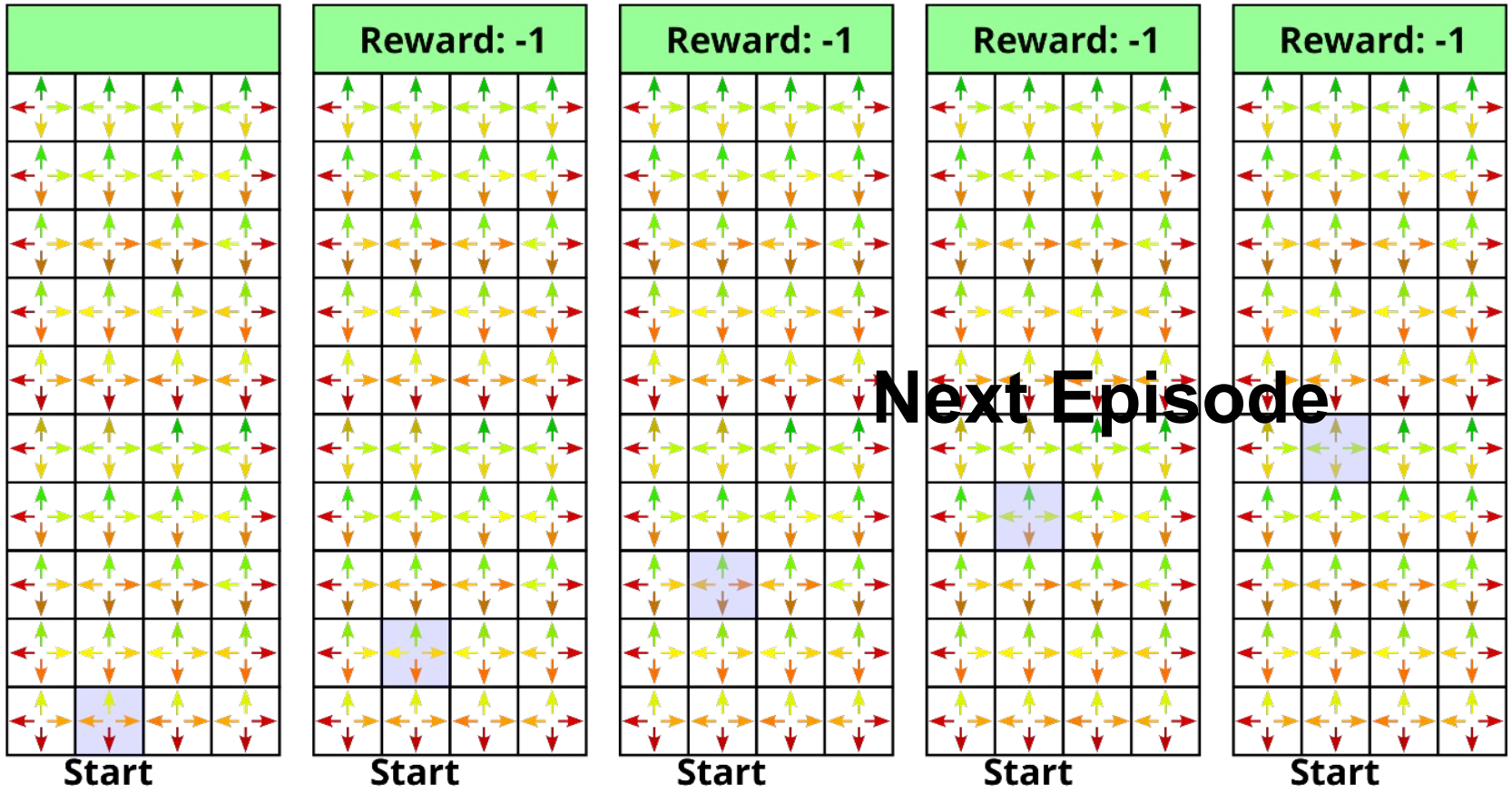

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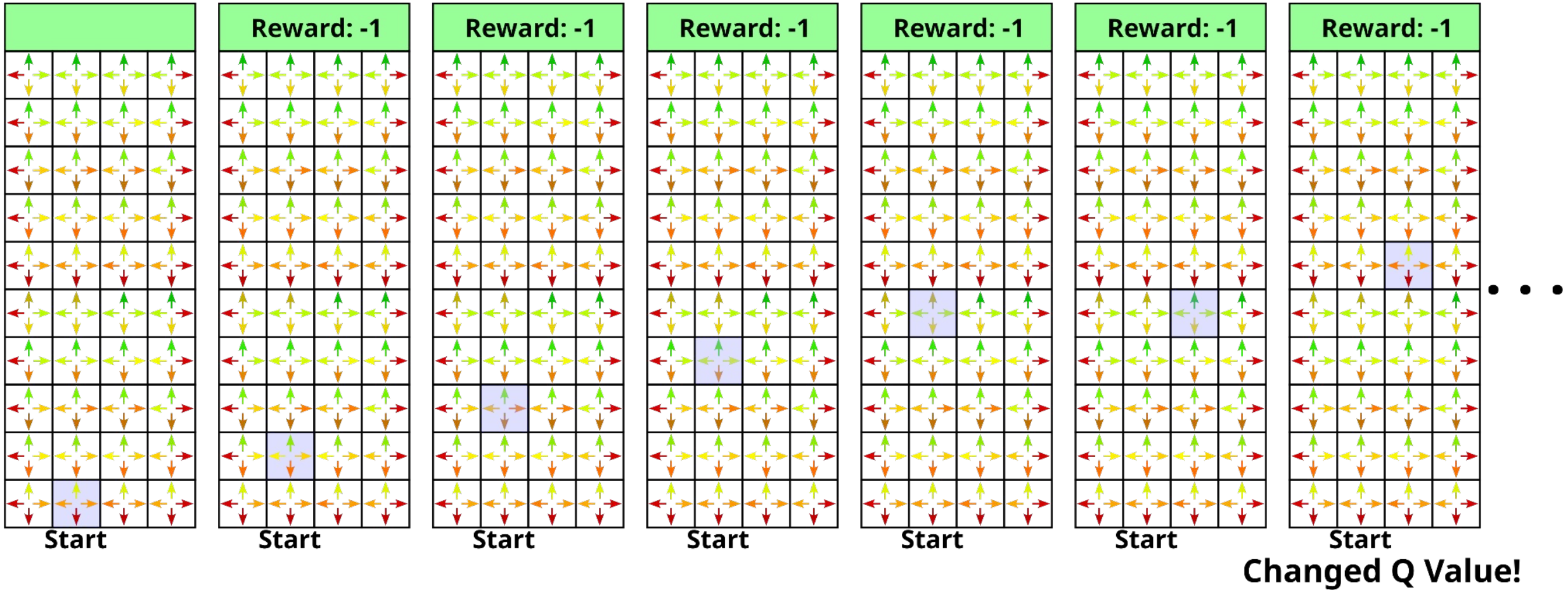
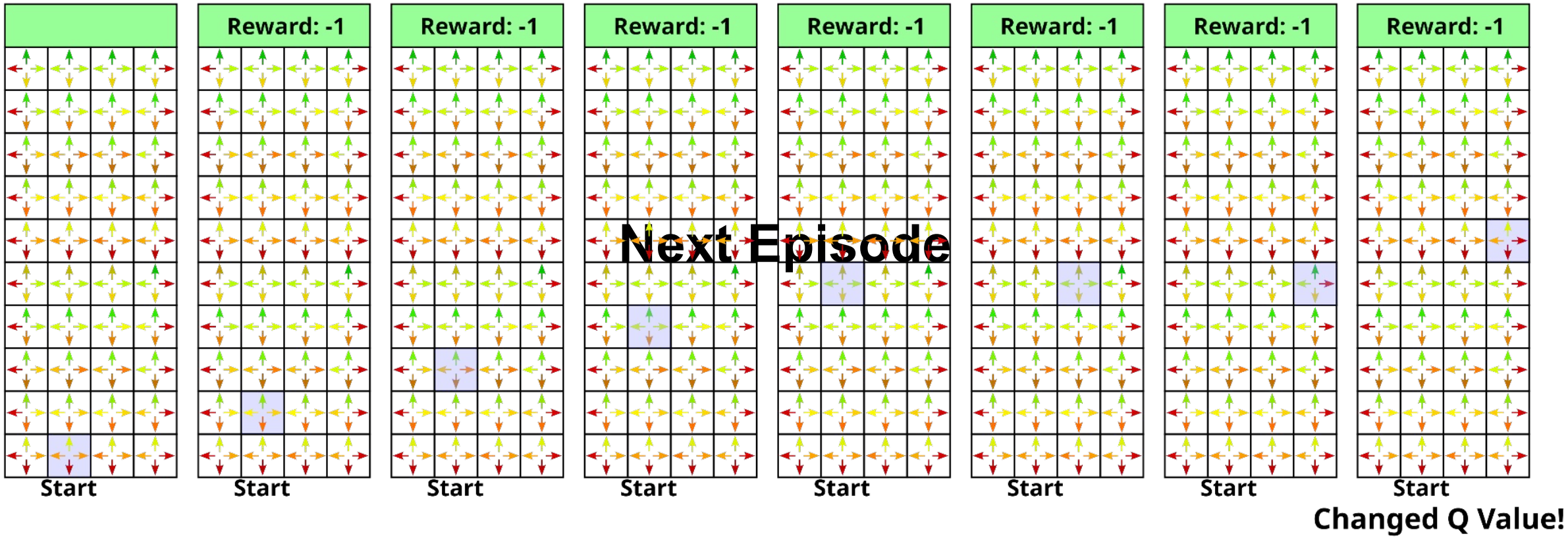


3rd Approach



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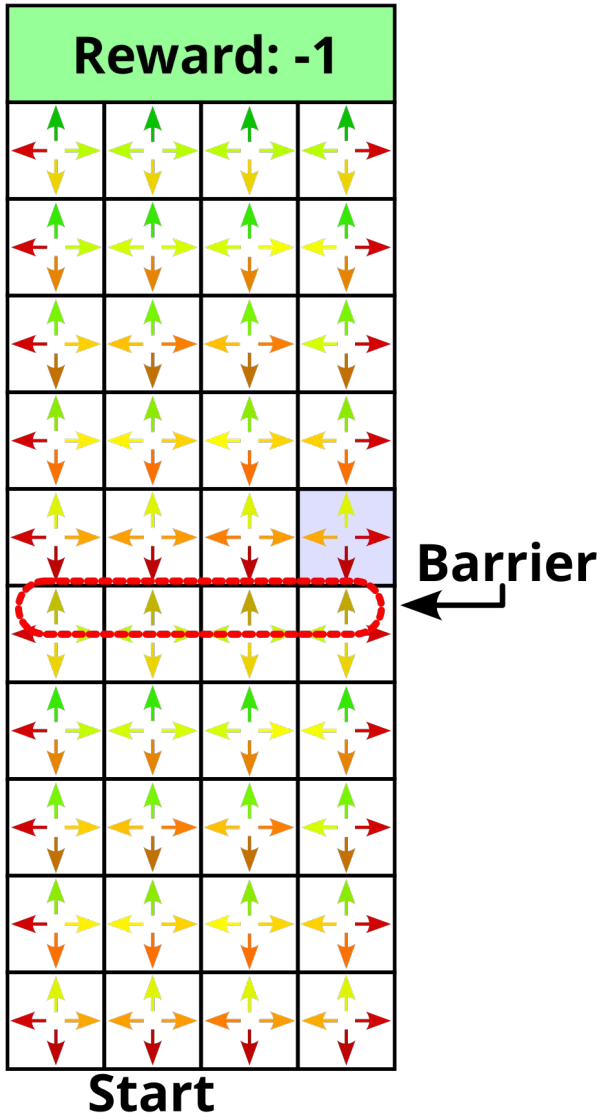
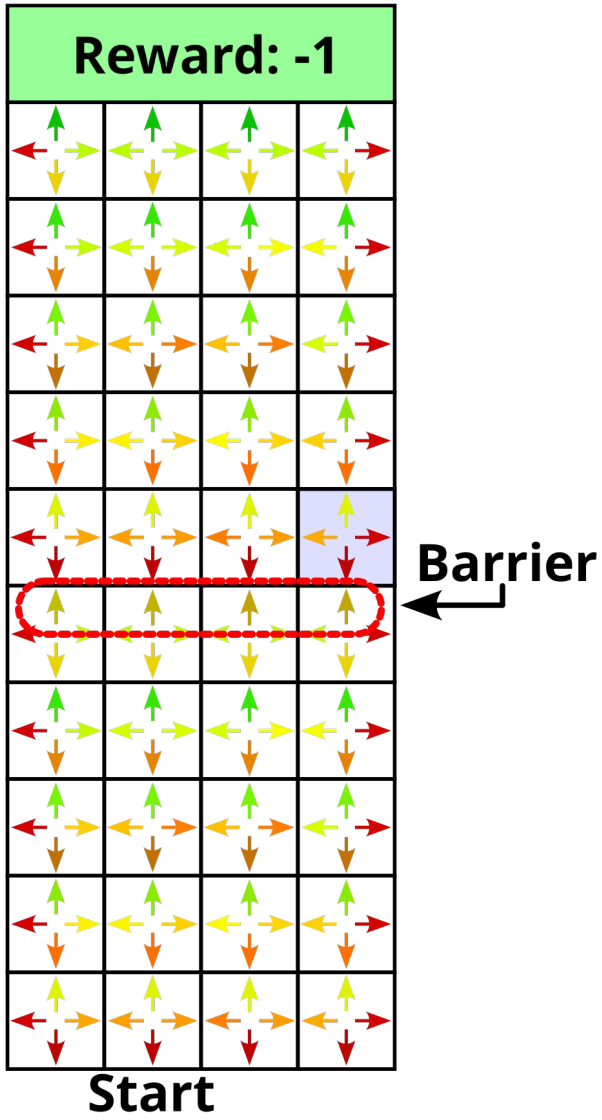


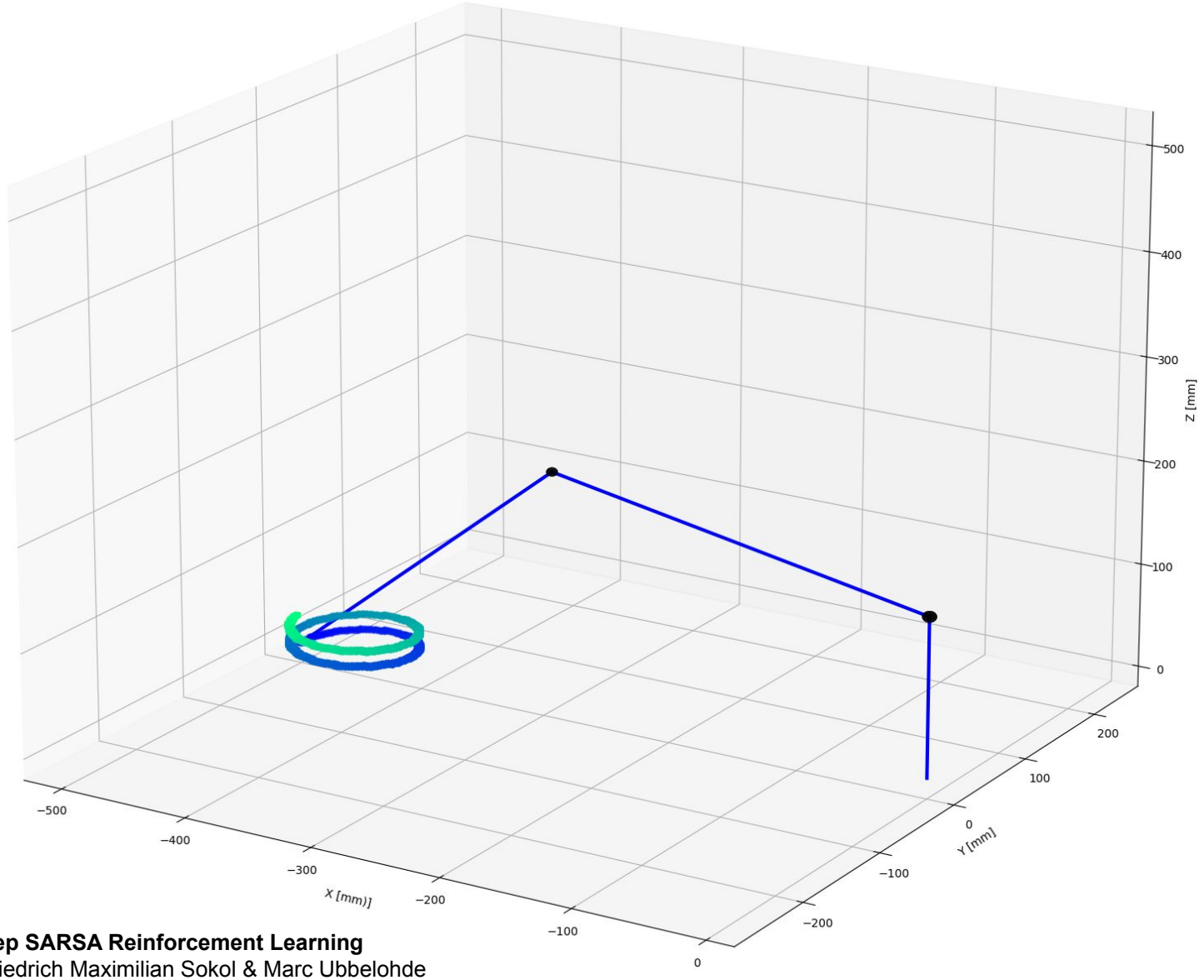
3rd Approach

- Good Q values unlearned
- Experimented with different reward structures
- No well working solution for this problem found
- **⇒ unsatisfactory**



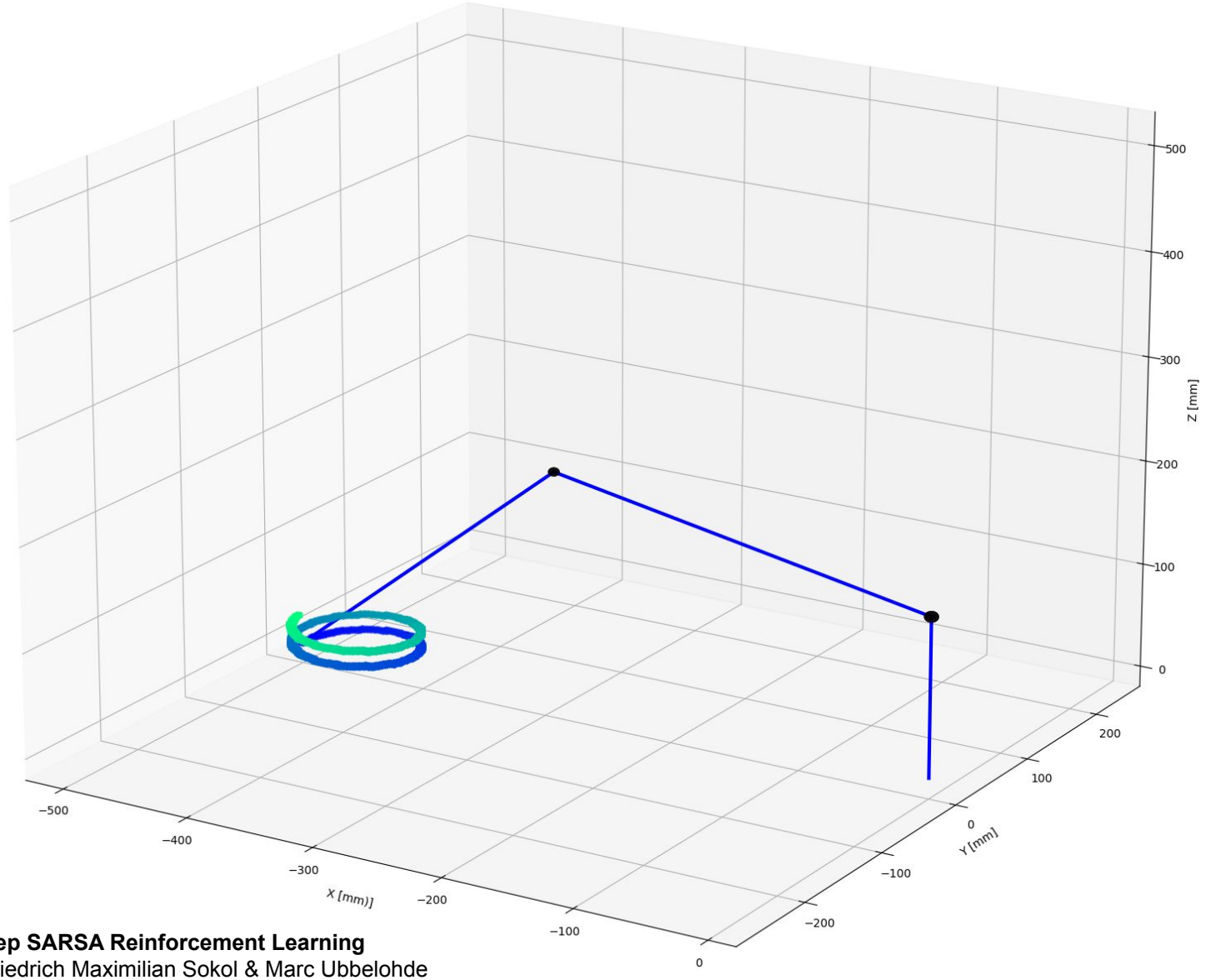
4th Approach

- Simplify robot:
  - Three axis
  - ⇒ $3^3 = 27$ Possible Moves per step



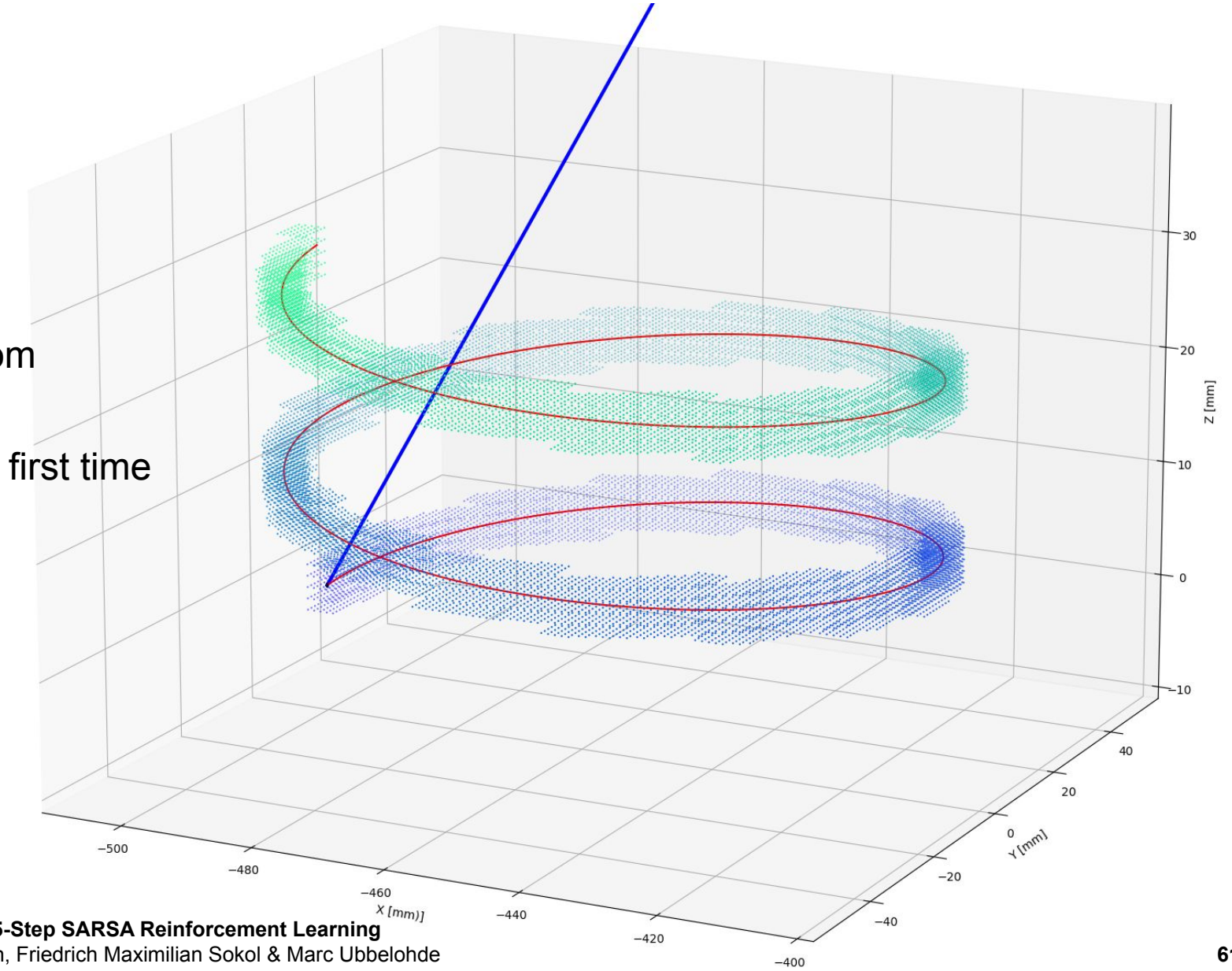
4th Approach

- Simplify robot:
  - Three axis
  - ⇒ $3^3 = 27$ Possible Moves per step
- Implement checkpoints
- Once a checkpoint in an episode is passed, resets only to checkpoint



4th Approach

- Revised reward system:
  - -500 for going out of bounds
  - -250 for moving backwards
  - Linear increase of step reward from -100 to 0 moving along helix
  - 0 for passing a checkpoint for the first time
  - 100 when in finishing voxels



4th Approach

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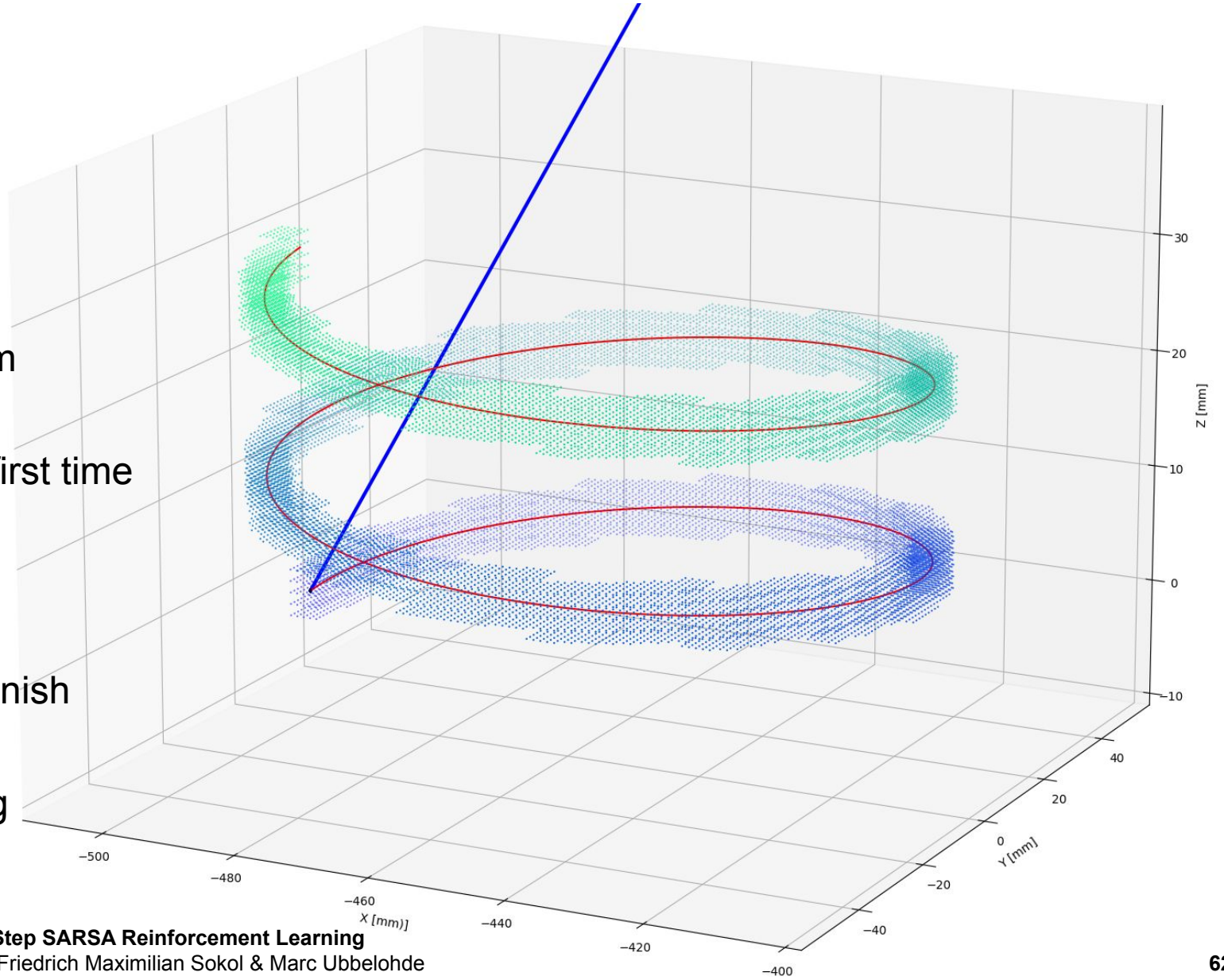
  - -500 for going out of bounds
  - -250 for moving backwards
  - Linear increase of step reward from -100 to 0 moving along helix
  - 0 for passing a checkpoint for the first time
  - 100 when in finishing voxels
- **Goals:**
  - Reward more aggressively and punish going into the wrong direction
  - Keep sectioning but still train using whole policy



4th Approach

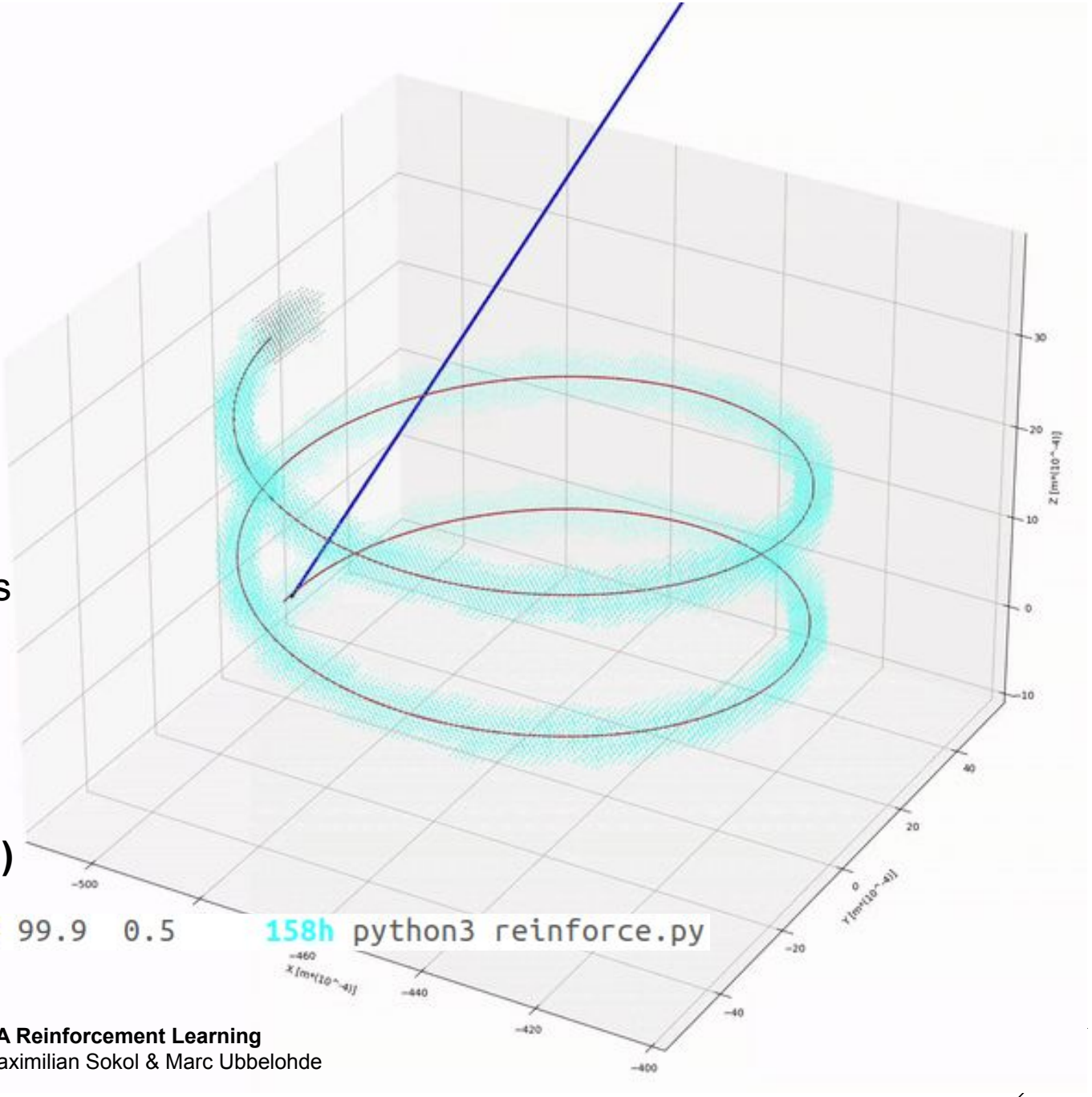
- **… after 5.5 hours of learning:**

This works!

- **Can we use this with the 6-Axis robot?**
- Forward kinematics for 6-Axis robot: 2 times as long
- Decision space: 3^3 times as large
- $5.5h \times 2 \times 3^3 = 297h = 12.375$ Days…

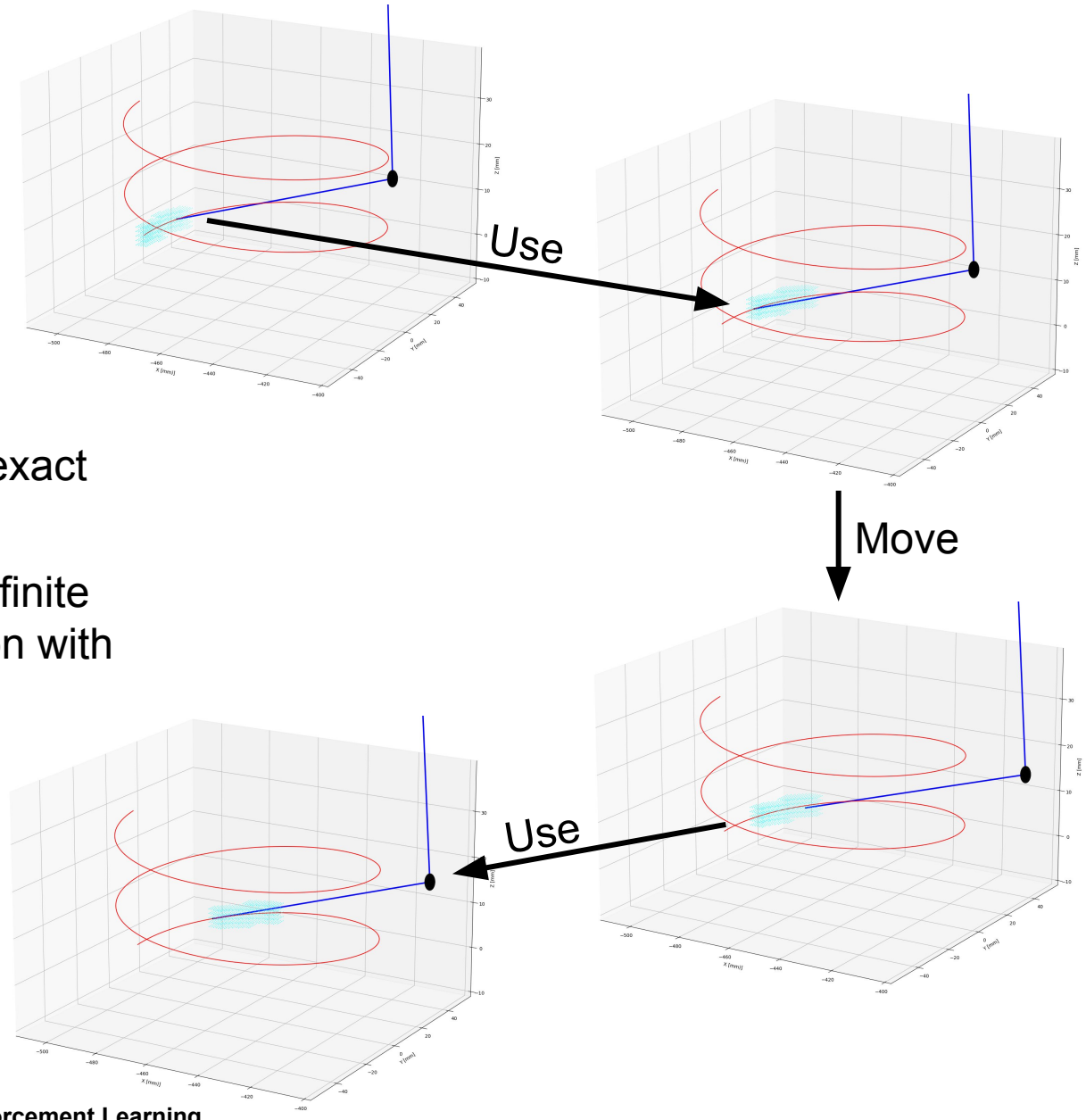
Let's say the computer is still calculating :)

```
235369 mle-admin  20   0 1170M  162M 22464 R 99.9  0.5     158h python3 reinforce.py
```



5th Approach

- **Go back to sectioning and parallelization**
- Learn 32 Sections in parallel
- Move the robot through each section
- Set starting angles of a following section to the exact finishing angles of the section before
- If Q values result in going out of bounds or an infinite loop, do 20 more training episodes of that section with the new starting point
- Repeat until all sections are traversed
- Stitch policies together



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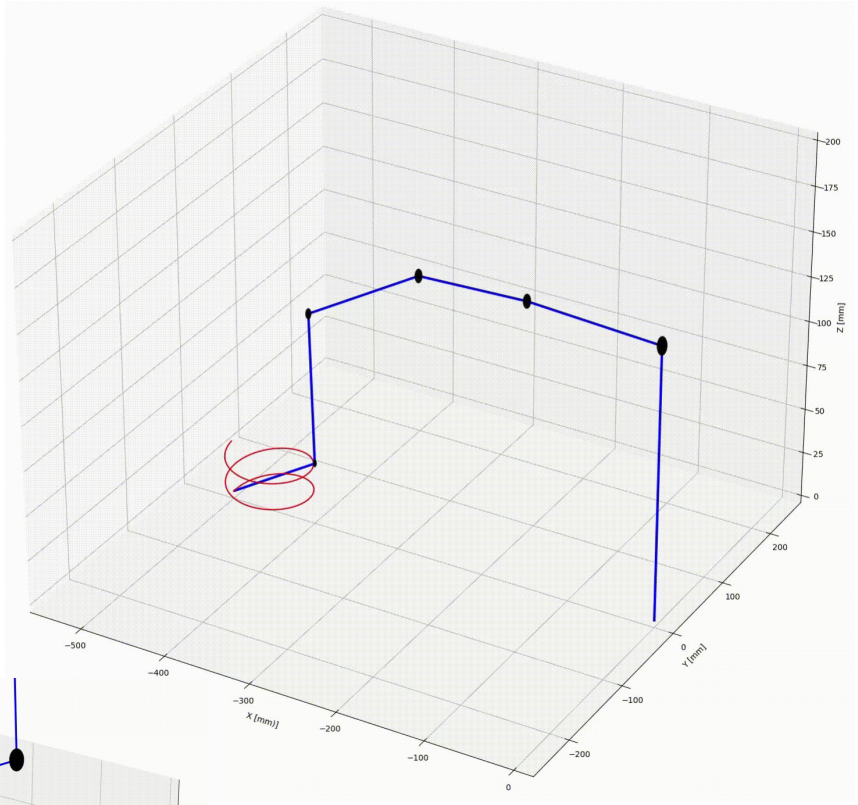
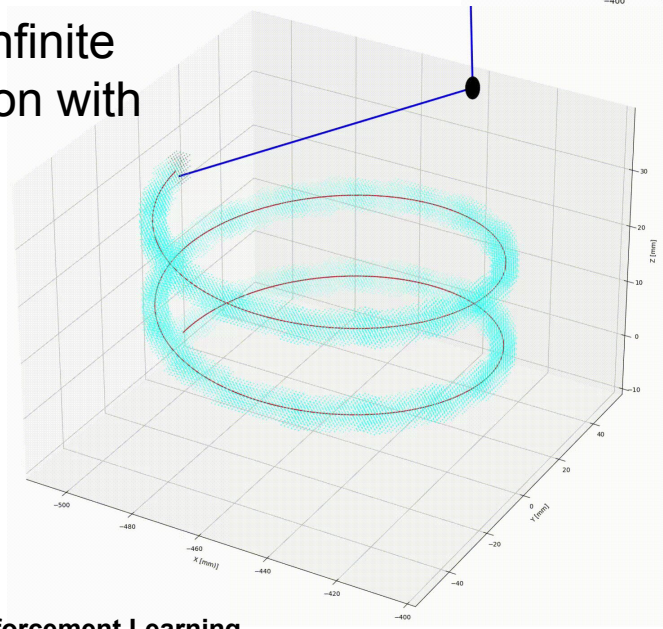
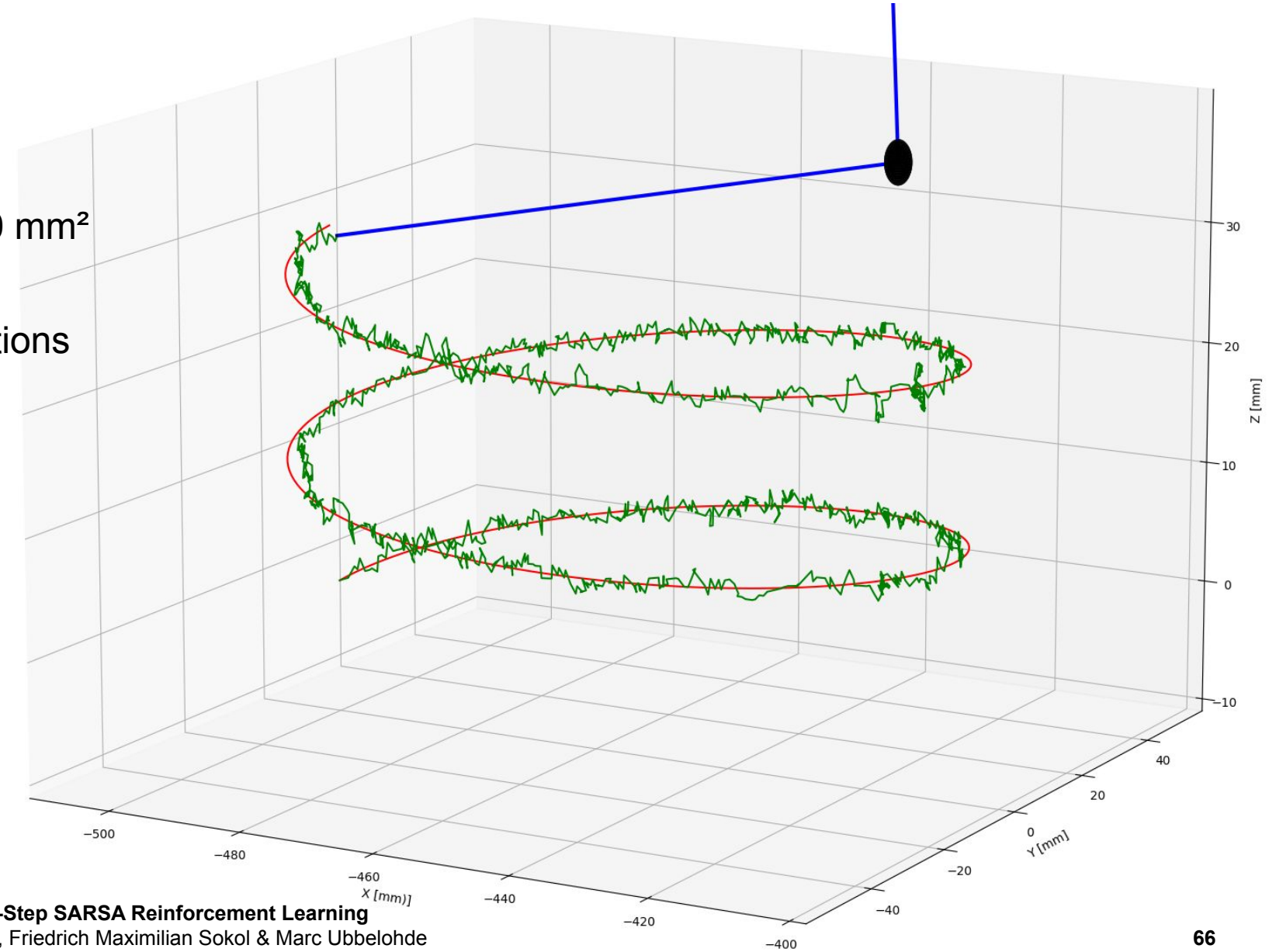
- Repeat until all sections are traversed
- Stitch policies together
- let robot traverse section by section





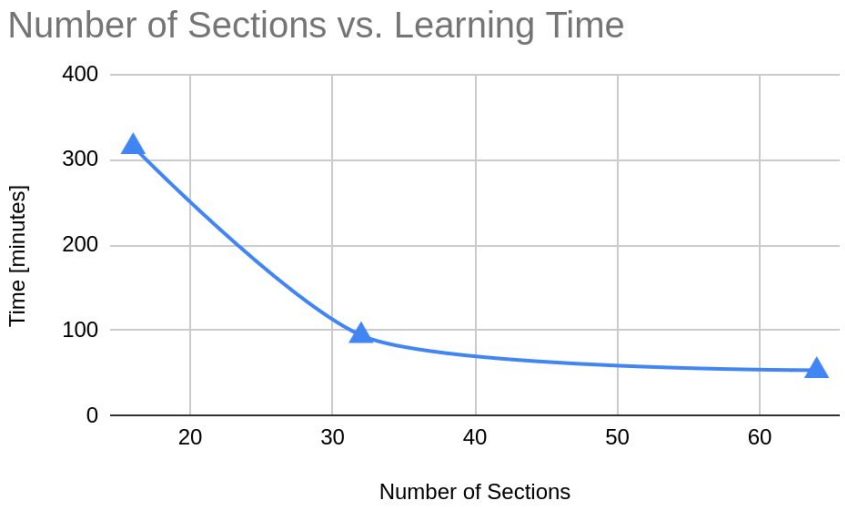
Result

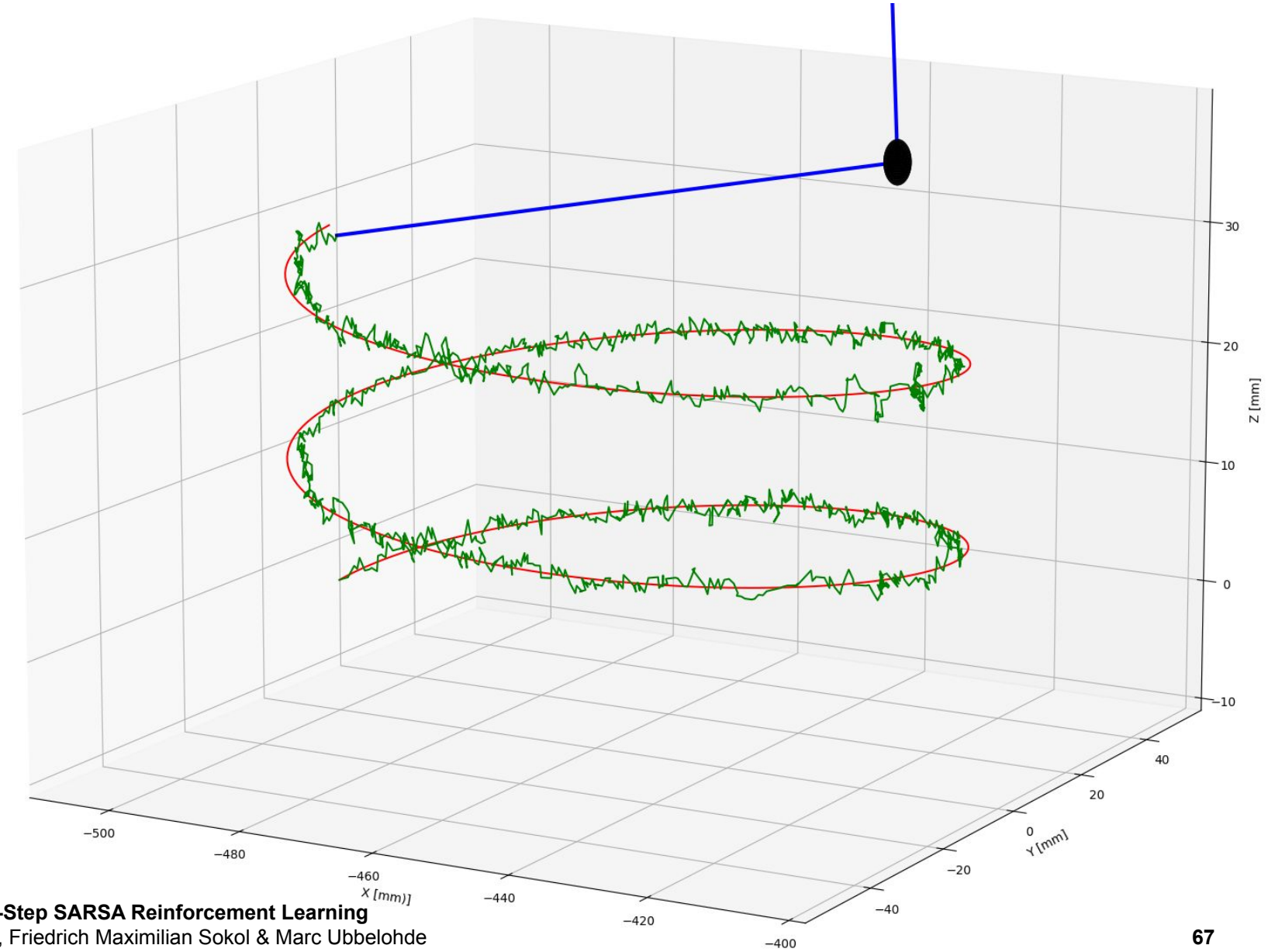
- MSE is between 42.38 mm² and 260 mm² over a total length of 377.52 mm
- time to learn ≈ 53 minutes at 64 sections
  - i9 12900k and 32 GBytes of RAM



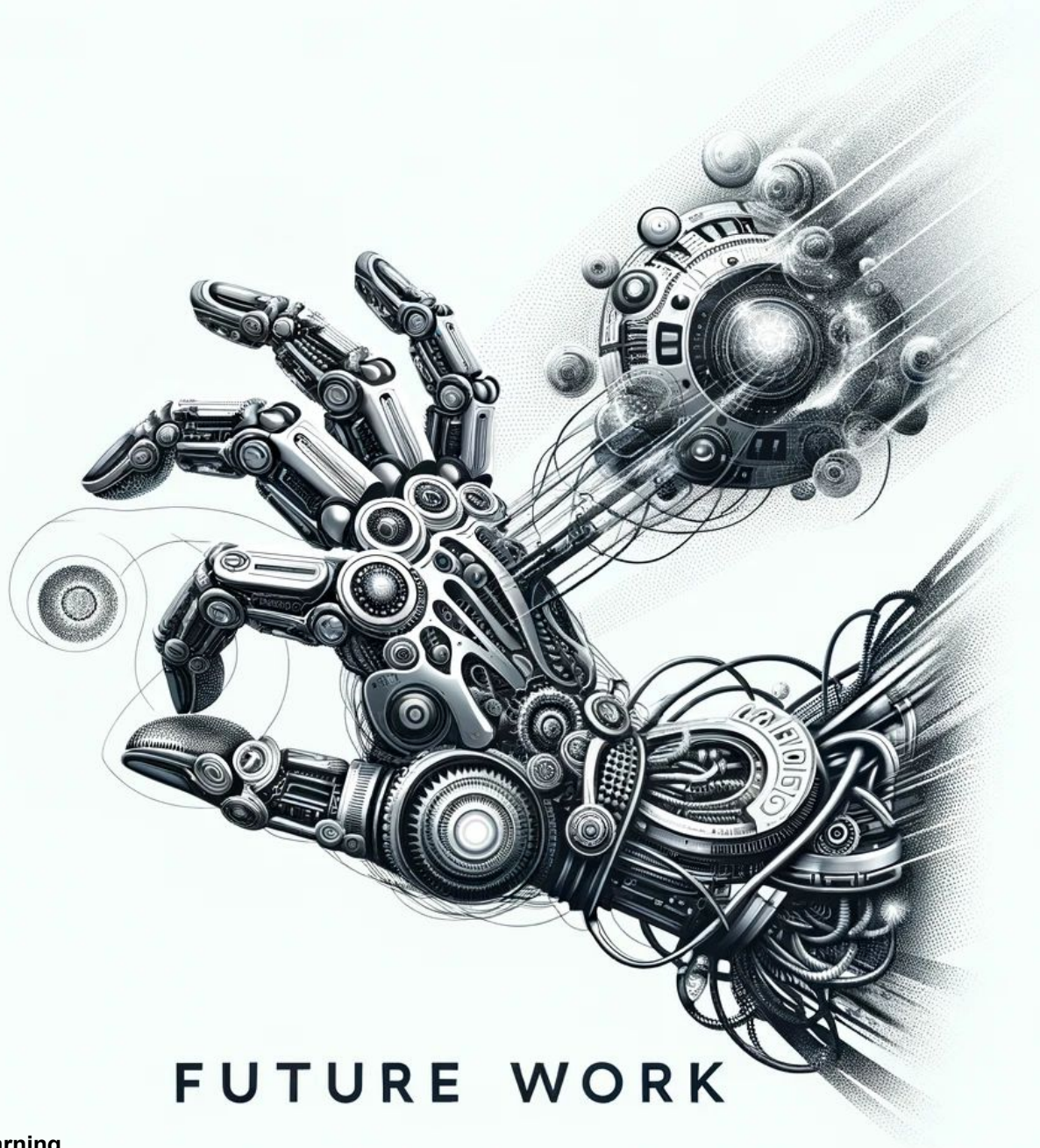
Result

Num Sections	Time (Minutes)	# Steps to traverse helix
16	315	1614
32	94	1511
64	53	2043





- Increase efficiency of the environment
  - Probably a lot of improvements can be done here
- Experiment with more reward structures
  - Reward structure is crucial in Reinforcement Learning (RL) Efficiency
- Remove Voxelization of space
  - Voxelization tends to increase MSE
  - Use a different RL method like Deep Reinforcement Learning to get rid of Voxelization



Source: Dall-E

Questions?

Source: Dall-E