Concours CNRS - CRCN 09/02

Leveraging kinematic analysis to transfer robot behavior learned from demonstration

Durgesh Haribhau Salunkhe

02 April, 2025

CNRS laboratory proposed:

1. ICube, Team RDH, Strasbourg
2. LAAS, Team Gepetto, Toulouse

Research Activity: Timeline

2018

Invest your talent in Italy scholarship

Erasmus Mundus Consortium scholarship

2020
Masters

First in class

Second in class
Best grades in thesis

ANR Project: ECARP

2023
Doctorate

2025
Postdoc

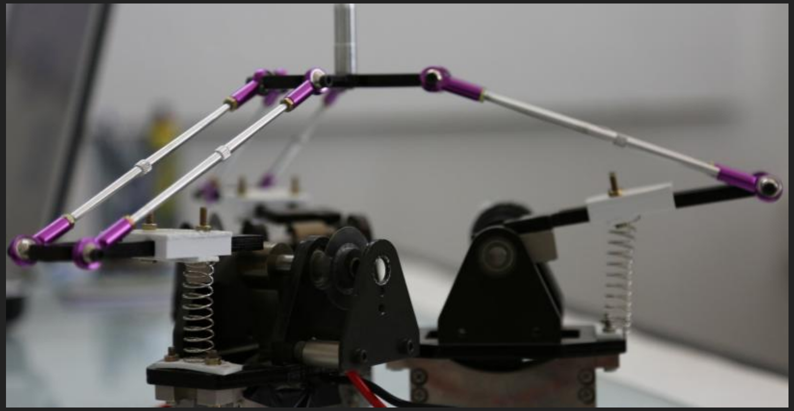
Research activity: Masters (2018 - 2020)

Parallel robots

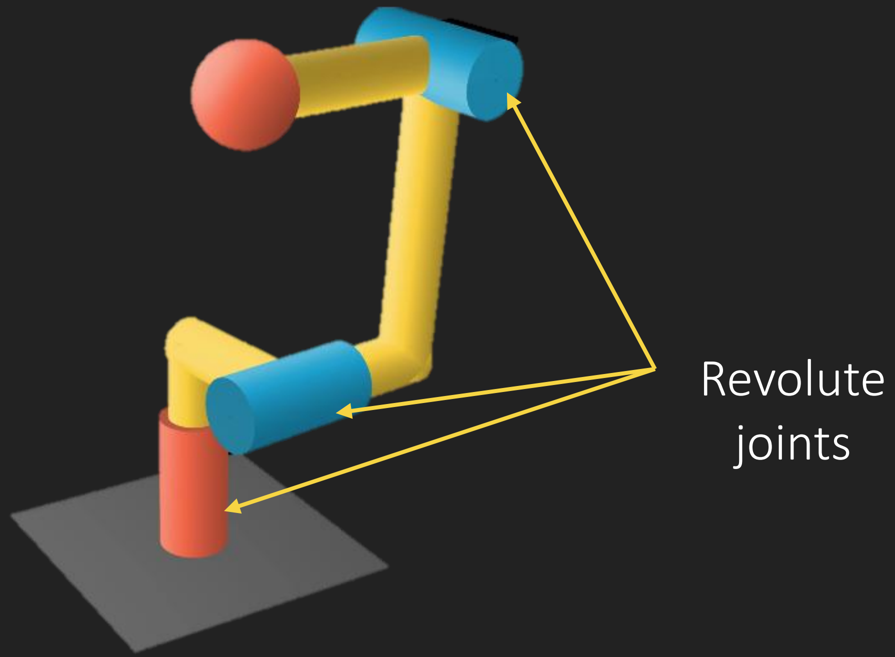
Medical robotics

Optimisation

1. Worked on active and passive compliance of parallel robots.
2. Studied workspace analysis relevant to otological and nasal surgery
3. Developed novel optimisation methodology to handle non-smooth constraints and complex objective function.



A 'nR' robot is a robot with 'n' revolute joints

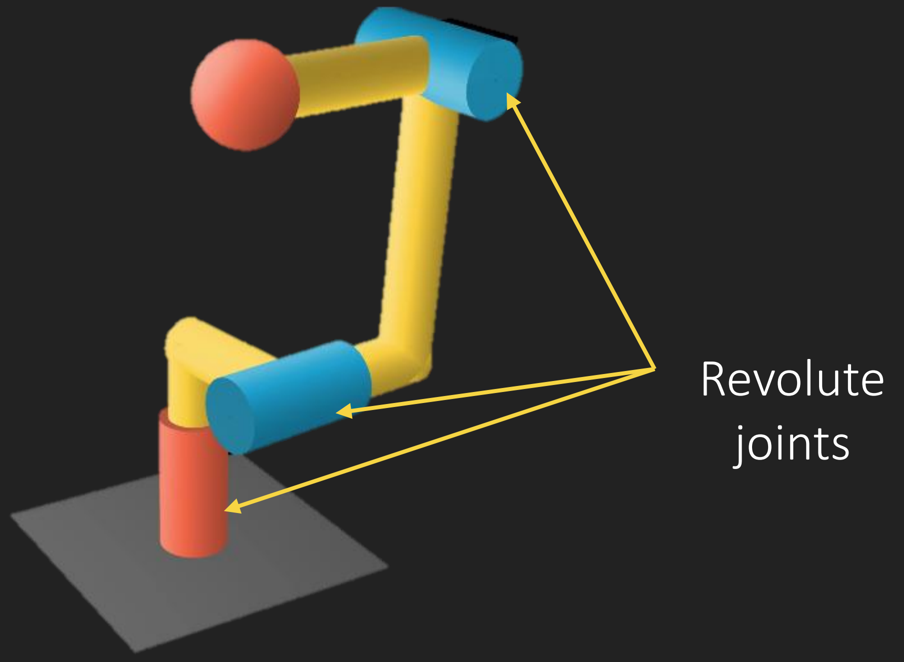


Example schematic of a 3R robot

Research activity: Doctorate (2020 - 2023)

A ‘nR’ robot is a robot with ‘n’ revolute joints

2R, 3R, 6R and 7R



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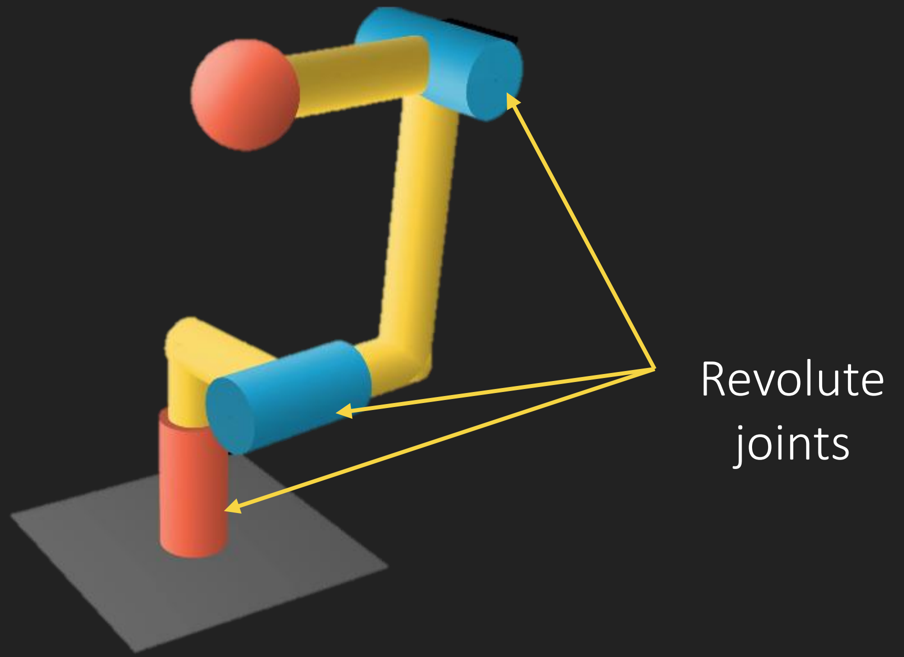

Example schematic of a 3R robot

> A singularity in a robot results in loss of degree of freedom, and the control becomes difficult on singularity.

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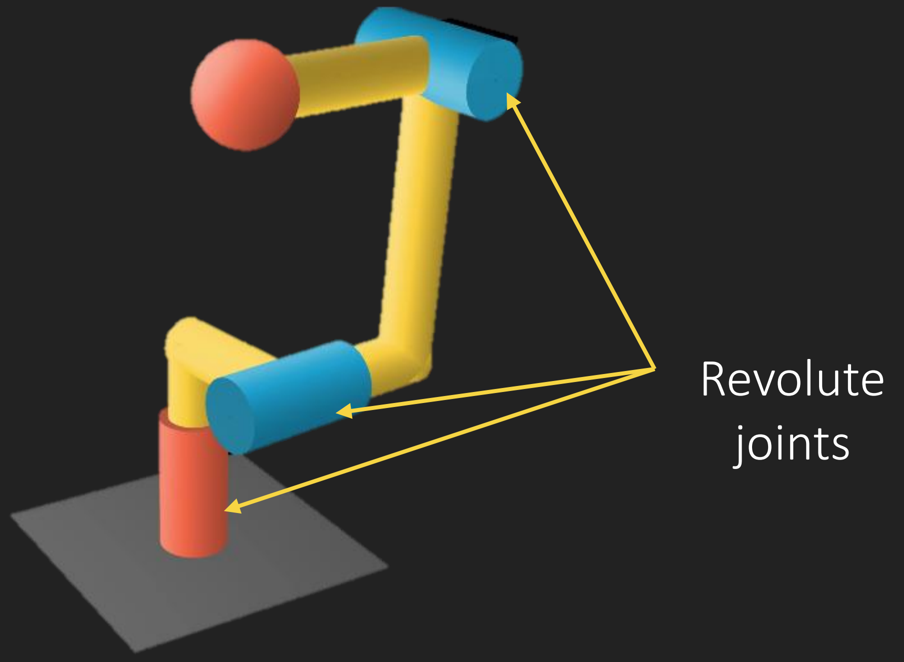

Example schematic of a 3R robot

> A singularity in a robot results in loss of degree of freedom, and the control becomes difficult on singularity.

> A robot with multiple inverse kinematic solutions in a singularity-free region is called a cuspidal robot (Wenger et El Omri, 1996).

Cuspidal robots: theoretical study, classification and application to commercial robots

Necessary and sufficient condition for a special case of 3R robot to be cuspidal (Wenger et El Omri, 1996)

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Necessary and sufficient condition for a special case of 3R robot to be cuspidal (Wenger et El Omri, 1996)

Sufficient condition for a generic 3R robot to be cuspidal (Corvez, 2004)

Cuspidal robots: theoretical study, classification and application to commercial robots

Necessary and sufficient condition for a special case of 3R robot to be cuspidal (Wenger et El Omri, 1996)

Sufficient condition for a generic 3R robot to be cuspidal (Corvez, 2004)

Cuspidality analysis of single 6R robot (Capco et al., 2020)

Cuspidal robots: theoretical study, classification and application to commercial robots

No results on a condition for a generic 3R robot to be cuspidal

Implications of cuspidal robots on the path planning of commercial robots?

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Necessary and sufficient condition using geometric analysis + homotopy-based analysis of 3R robots (MMT 2022, ARK 2022)

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Implications of cuspidal robots on the path planning of commercial robots?

Study workspace and types of paths for generic 6R robots (ICRA 2023, IJRR 2024)

Research activity: Doctorate (2020 - 2023)

Cuspidal robots

Path planning

Kinematic analysis

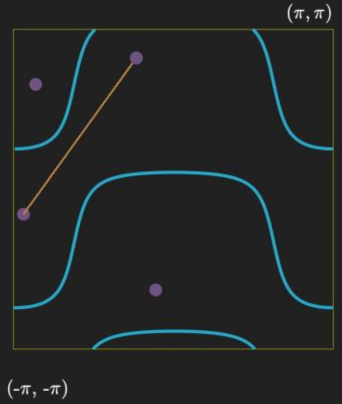
Theoretical contribution:

1. Necessary and sufficient condition for a generic 3R robot to be cuspidal

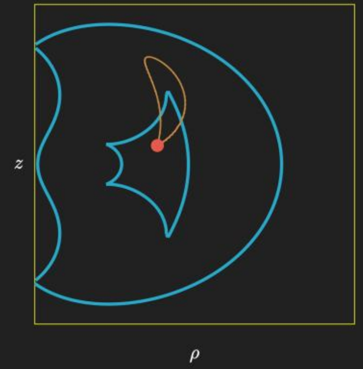
2. Proof of existence of reduced aspects in generic 3R robots.

Practical contribution:

1. Develop a unified framework for nonredundant robots with safety guaranteed path planning.



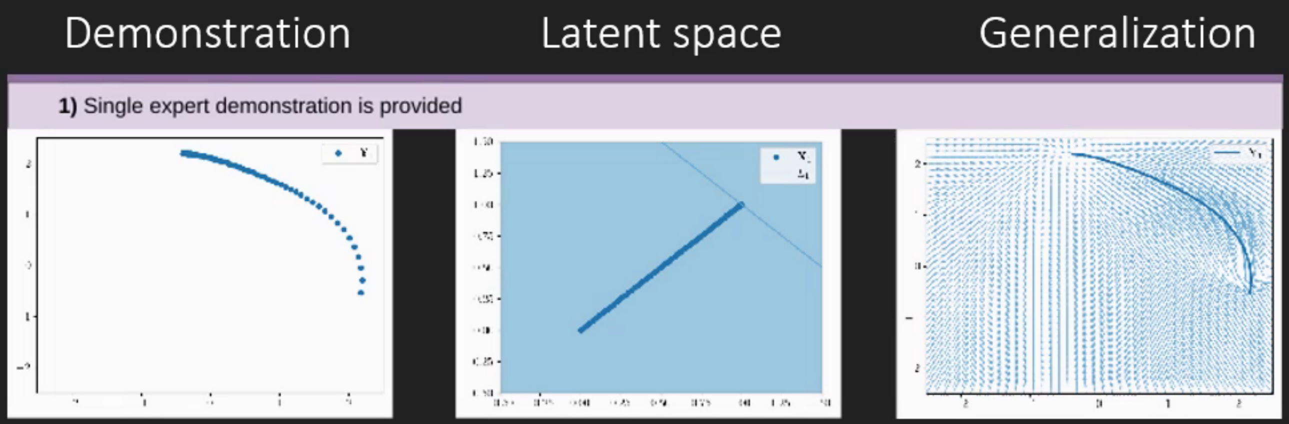
joint space

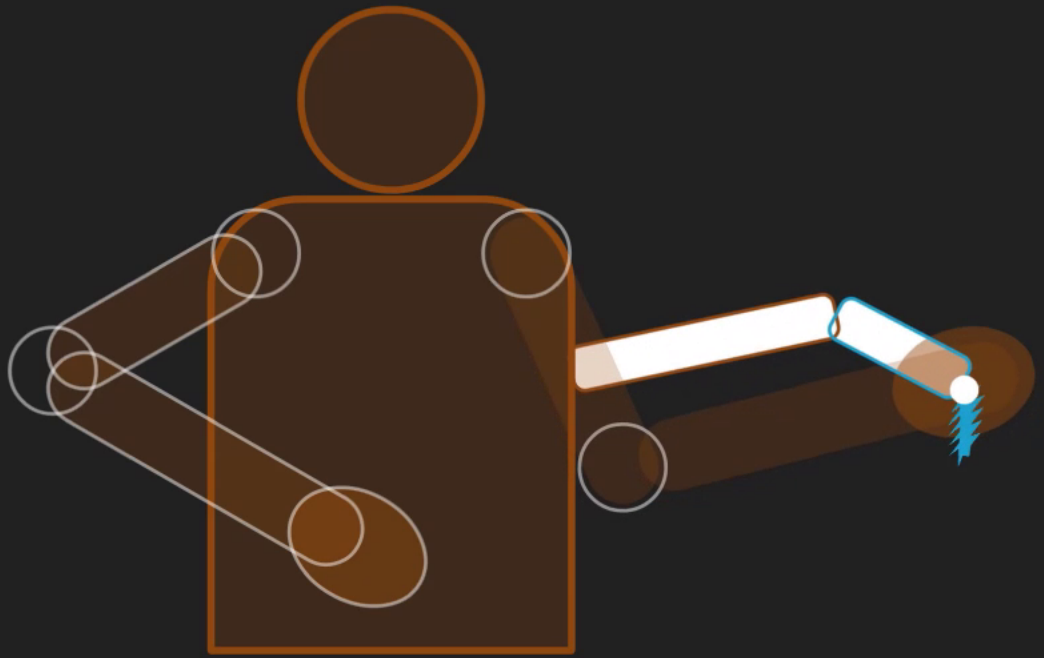


work space projection on ρ-z plane ($\rho = \sqrt{x^2 + y^2}$)

Learning from demonstration

The demonstration is embedded as a dynamical system for position and velocity replication.





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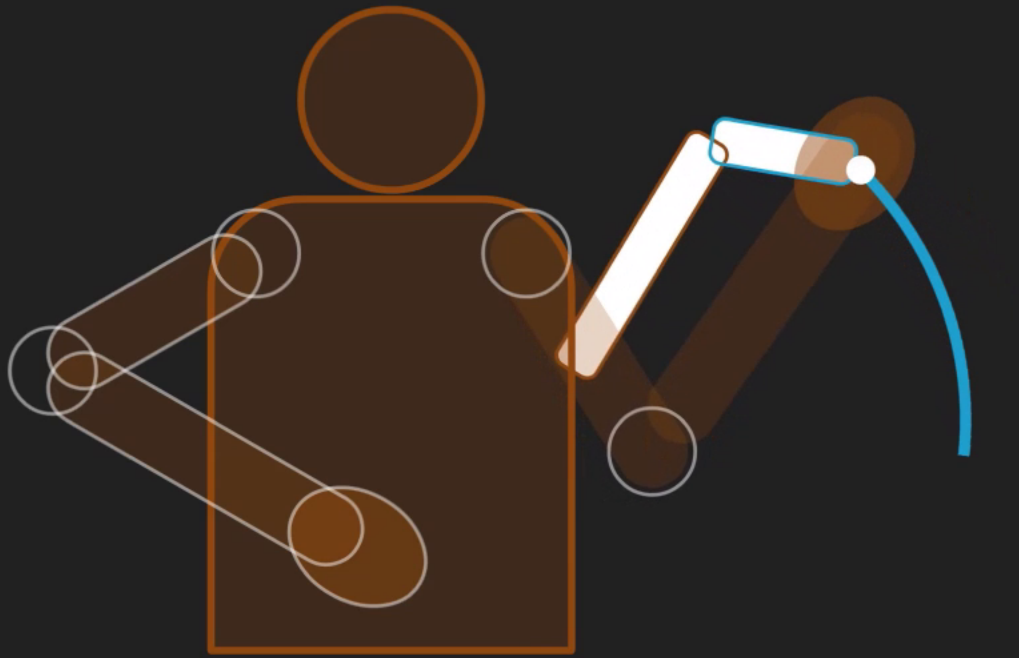

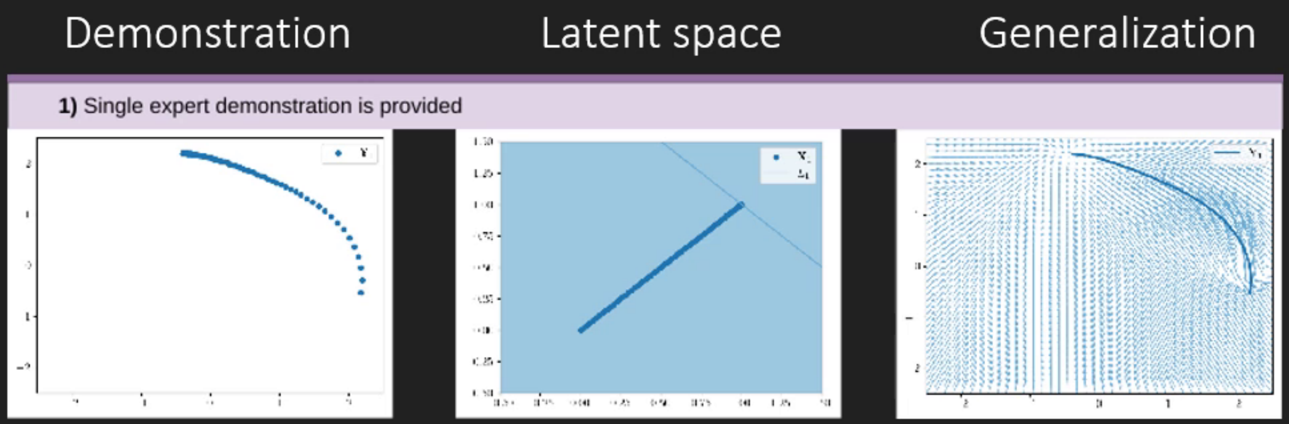

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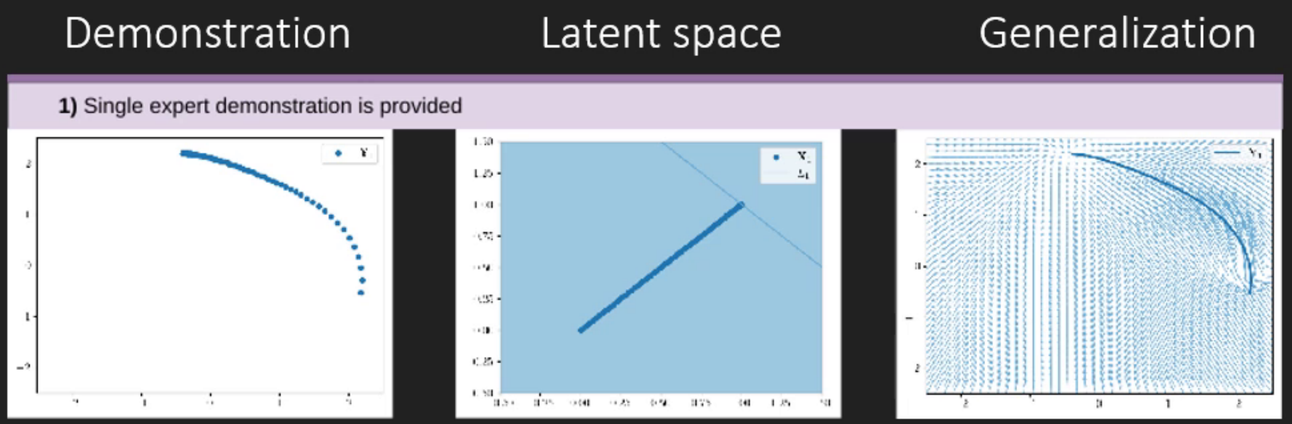

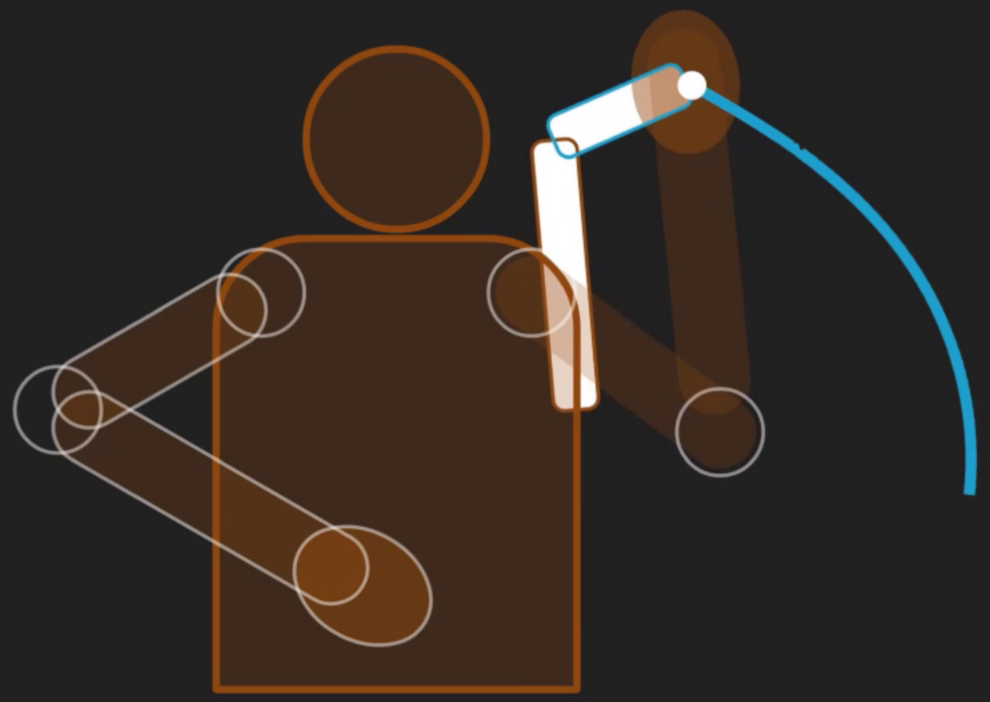

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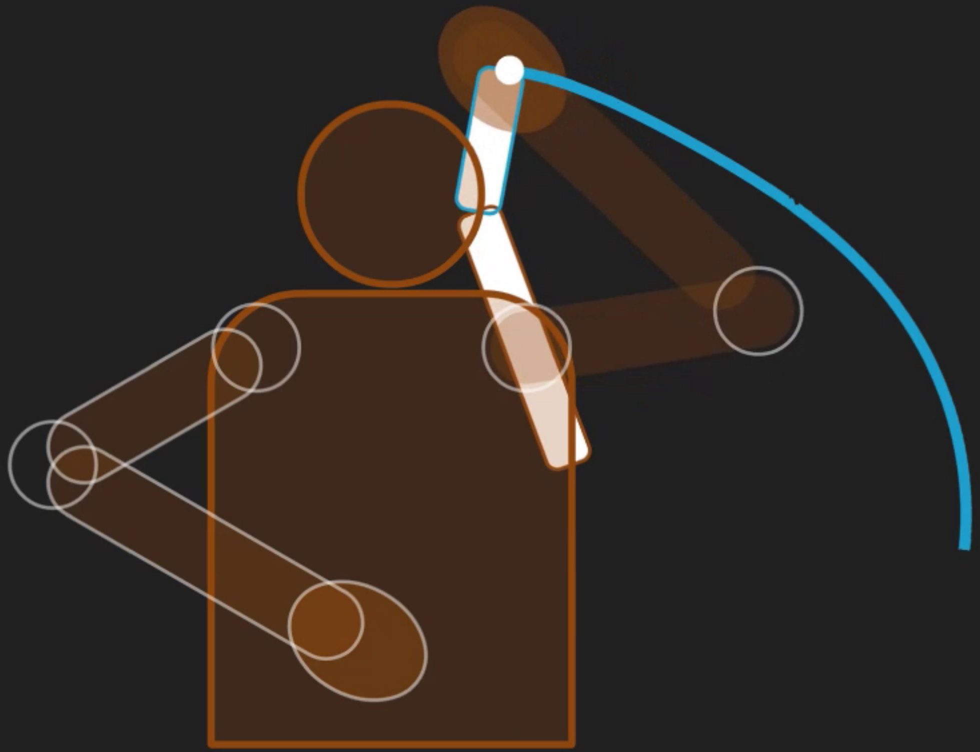

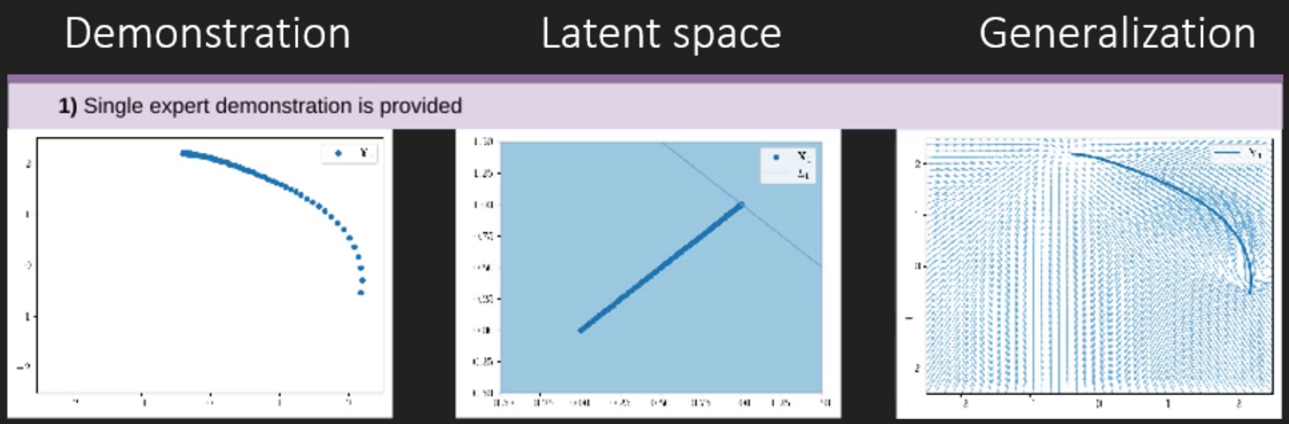

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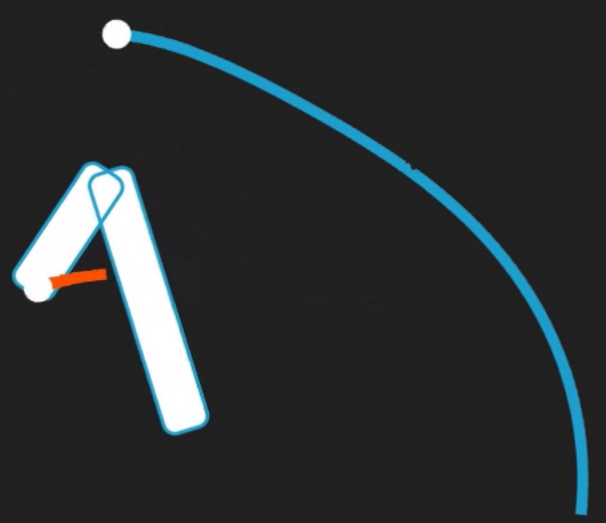

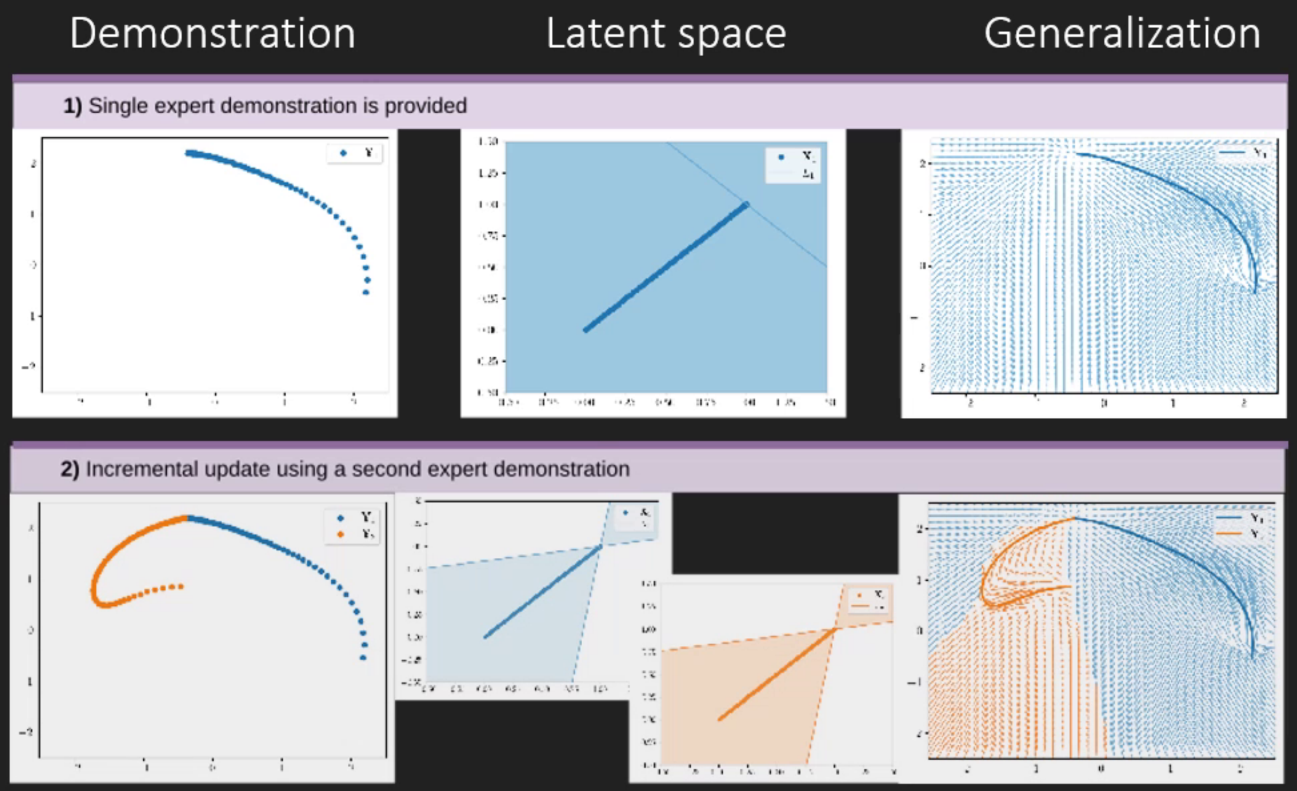

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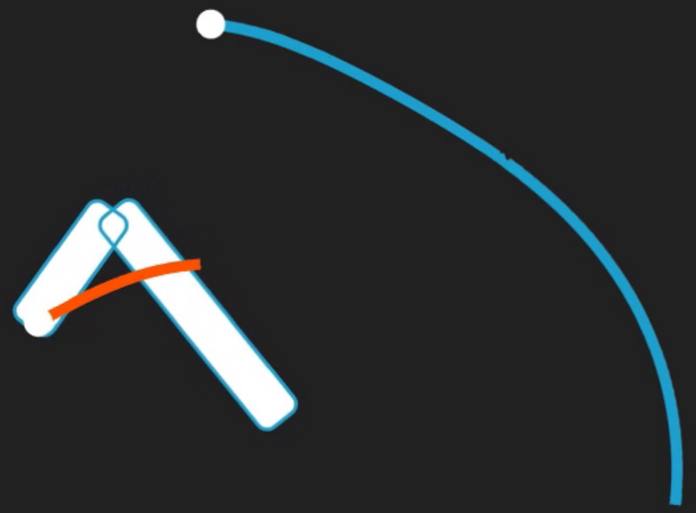

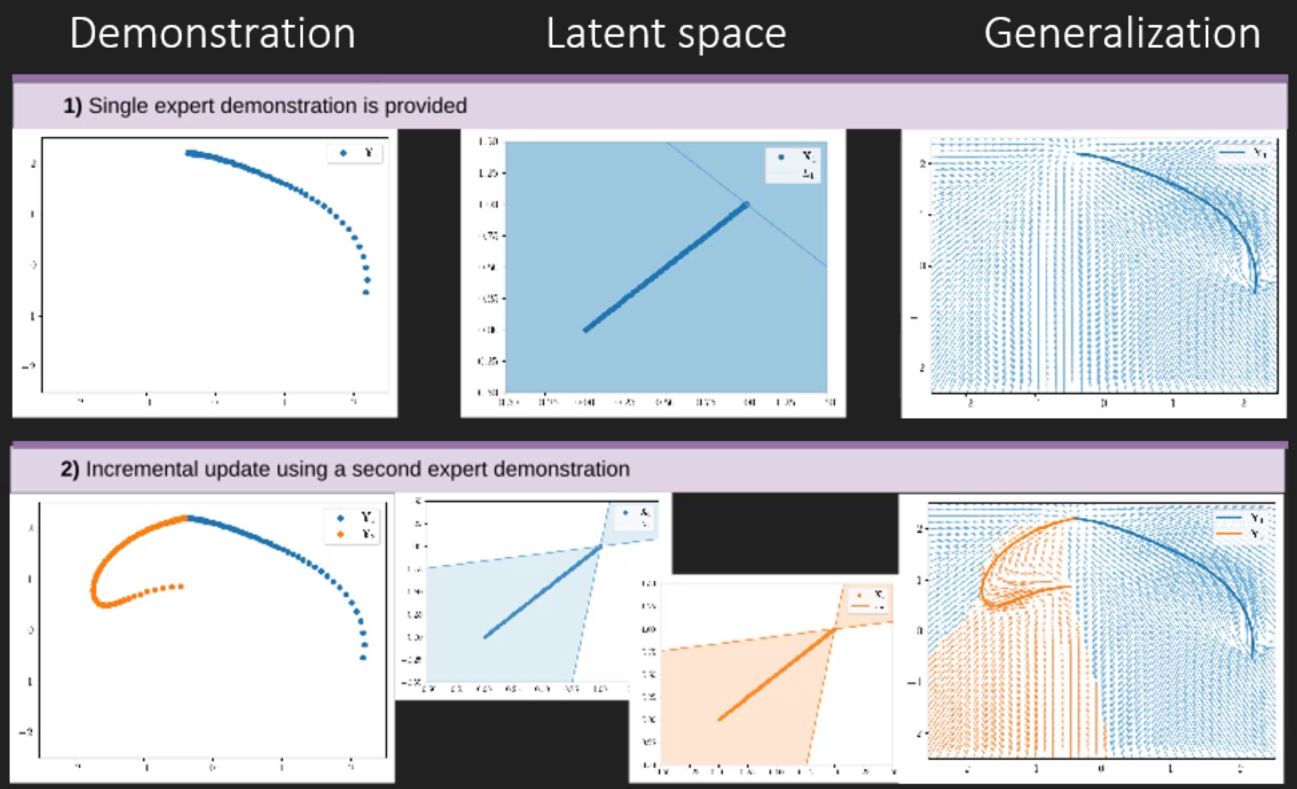

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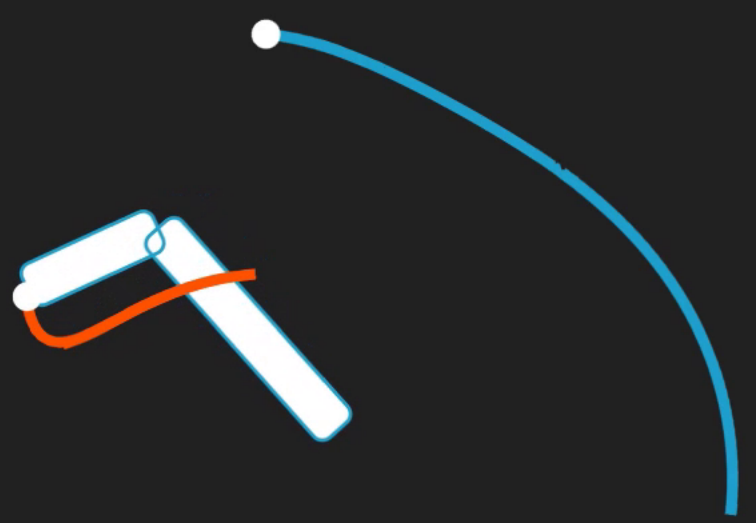

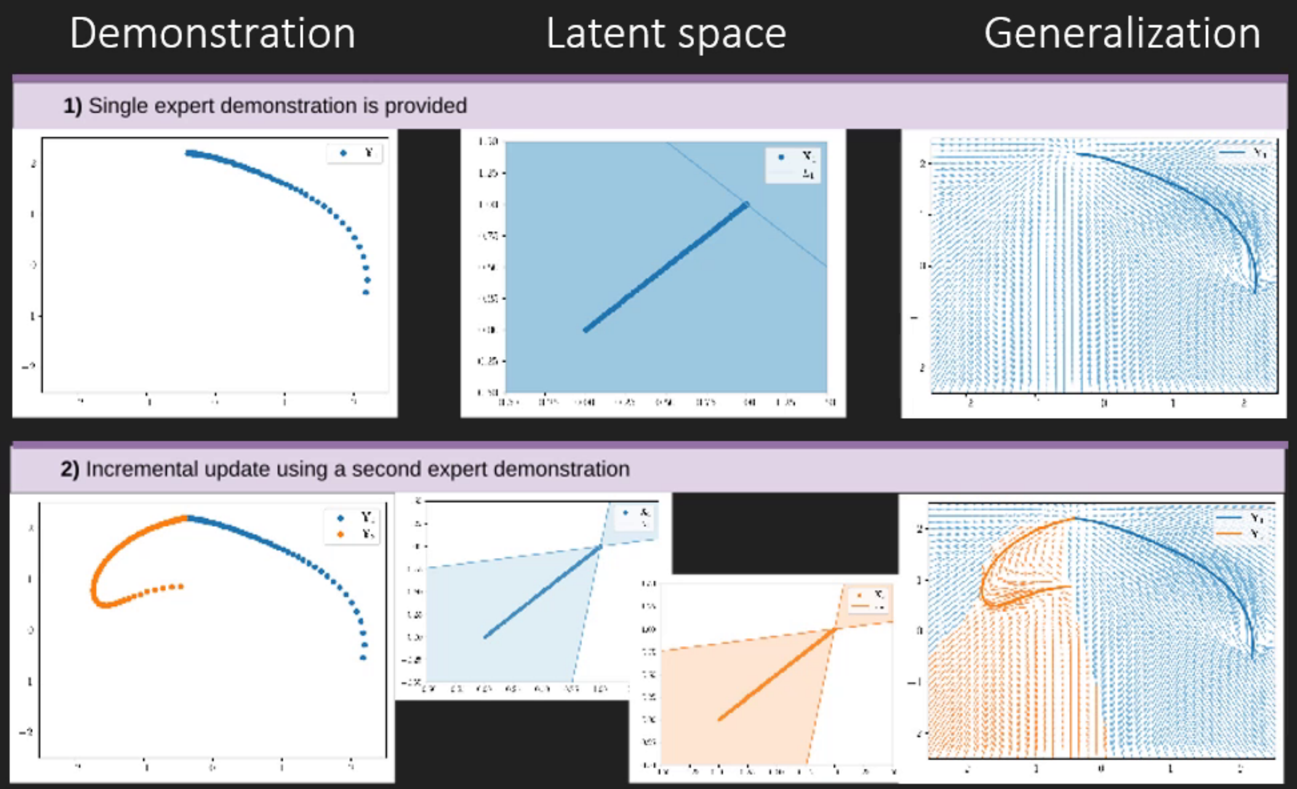

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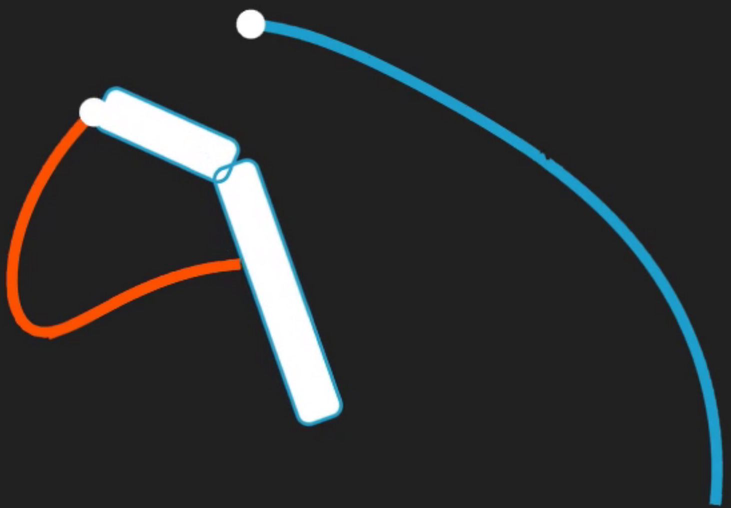

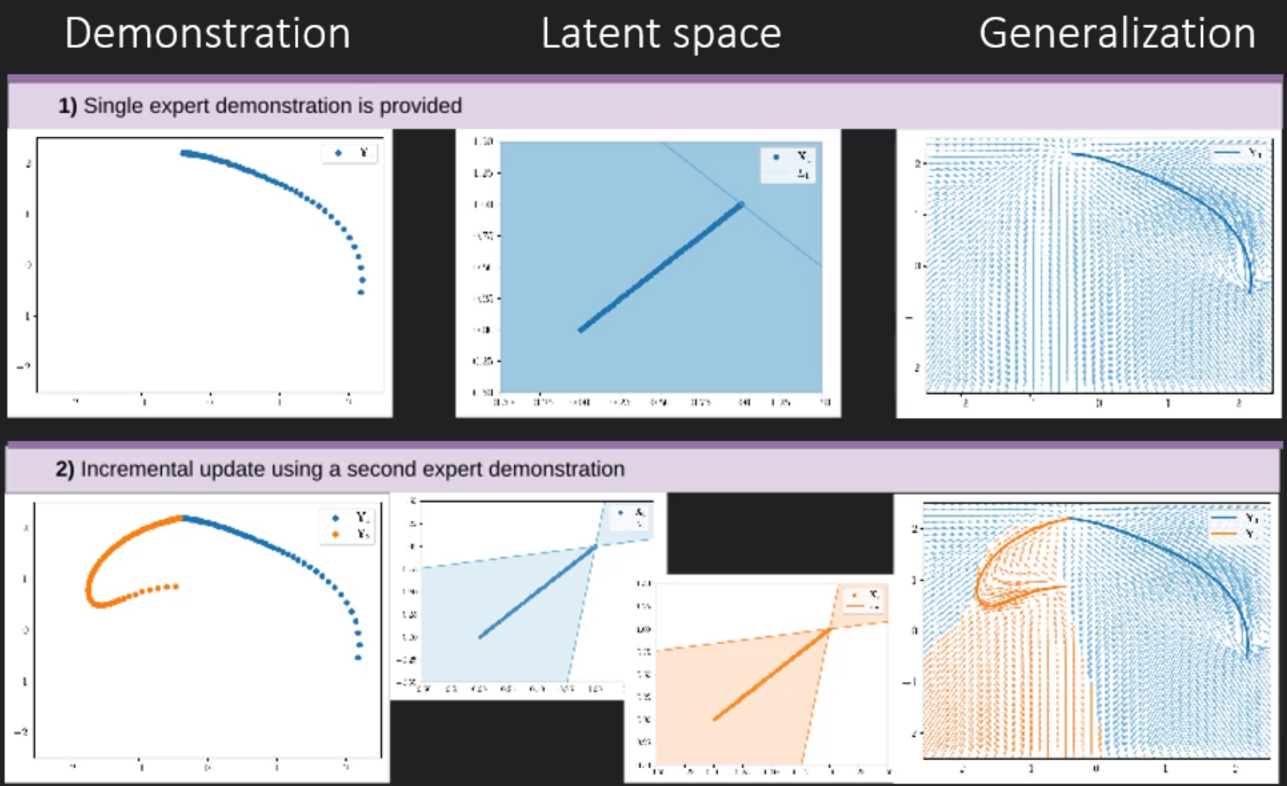

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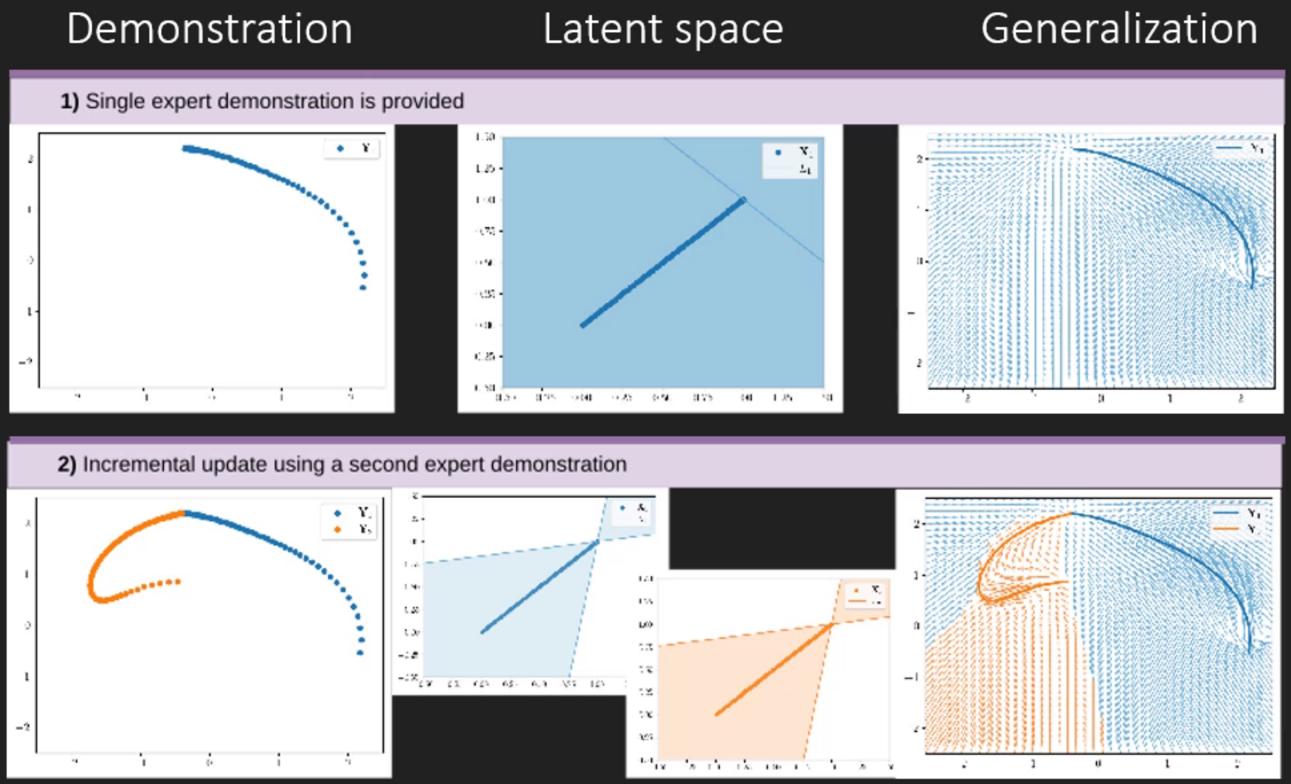
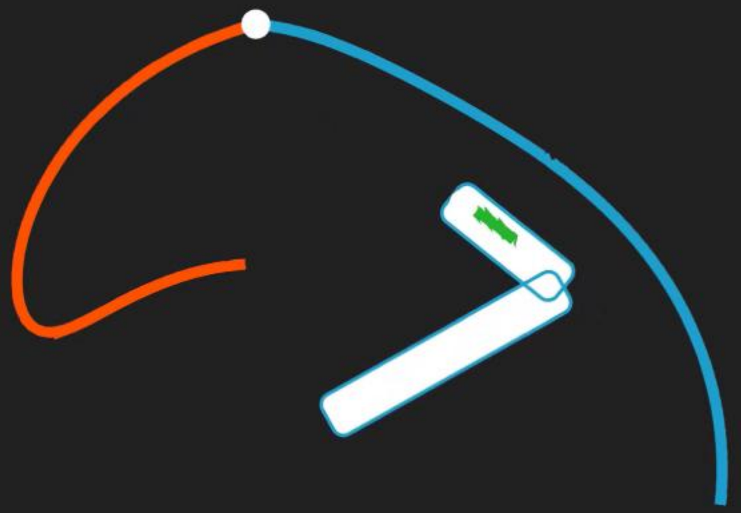
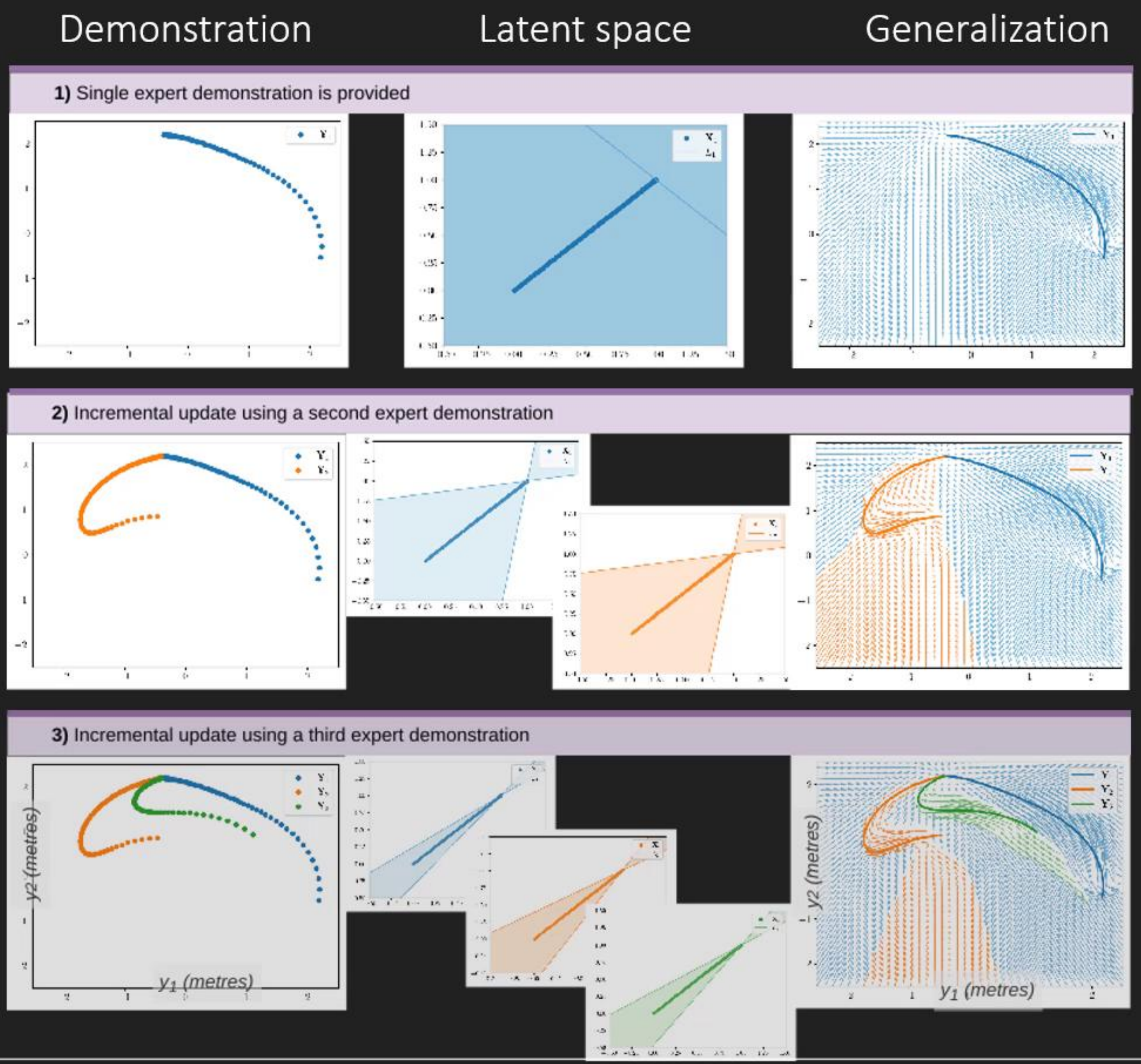


Learning from demonstration

Parameter efficient generalization that guarantees replication of all demonstrations.





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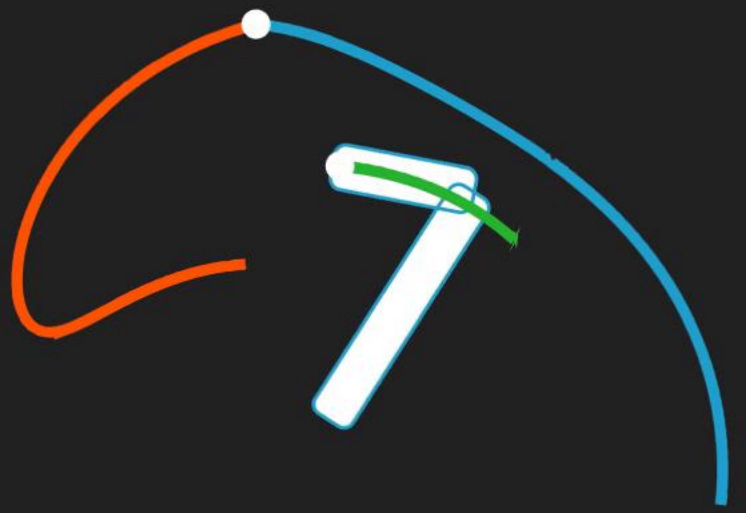

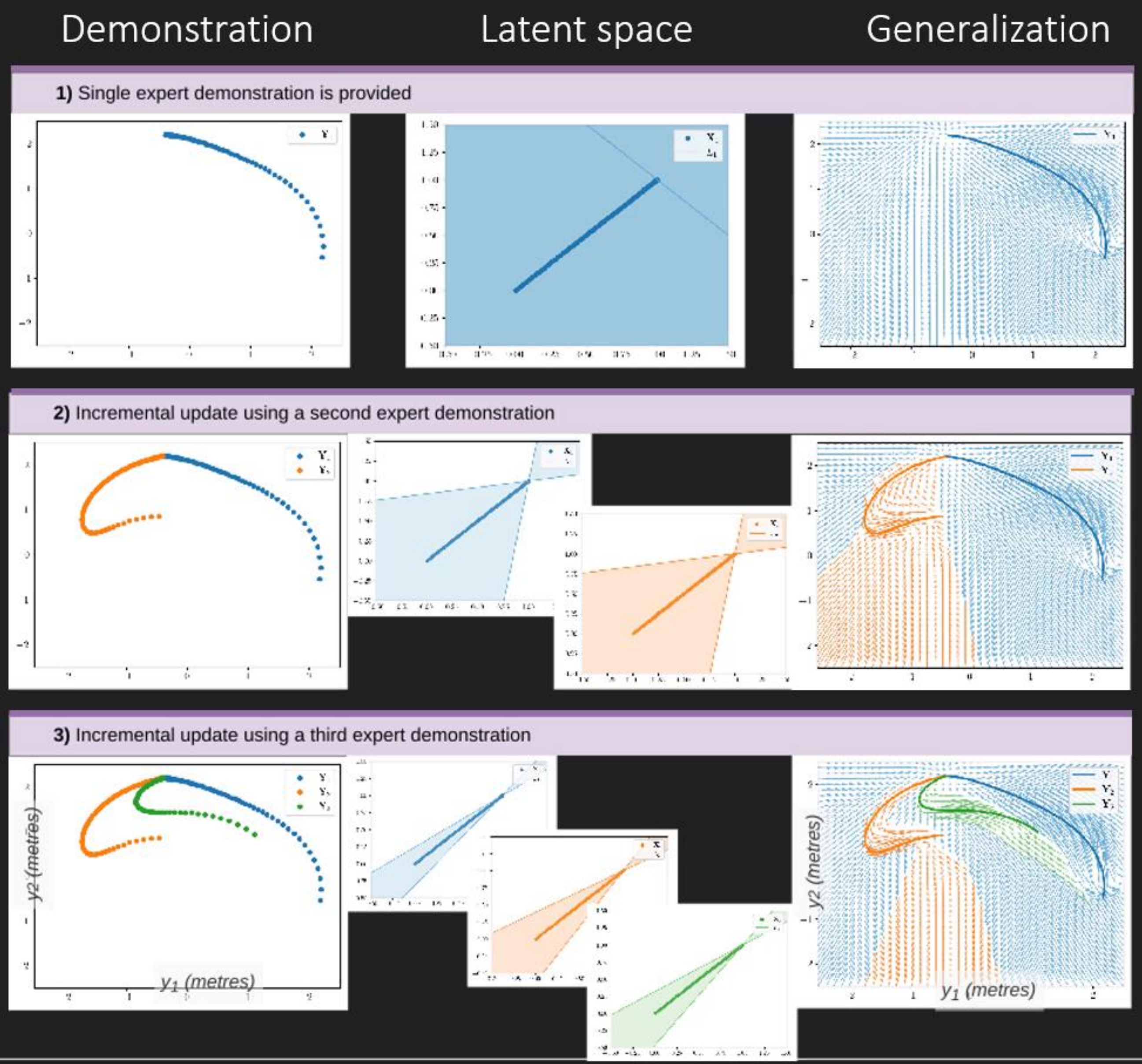

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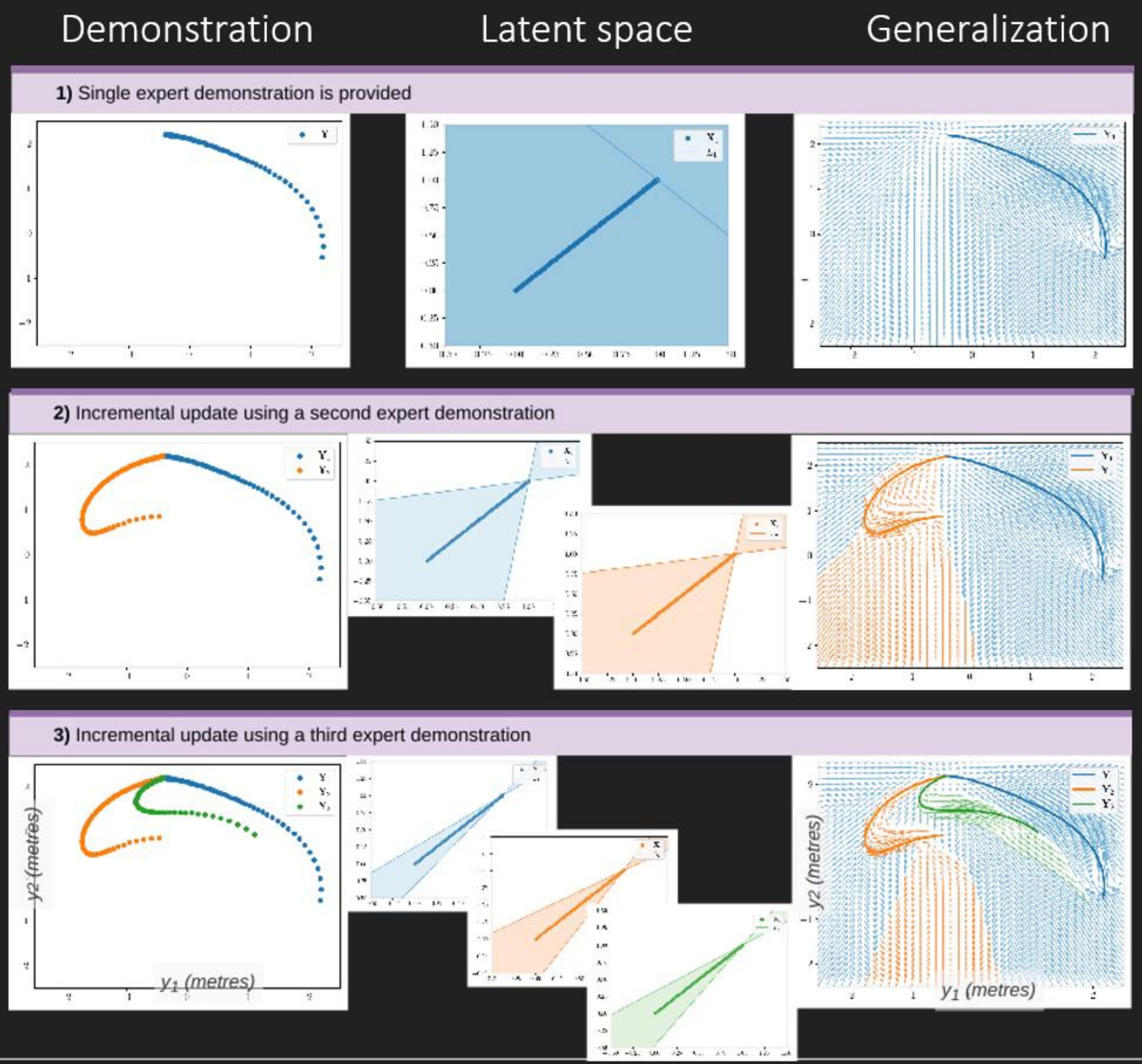

EPFL

Learning from demonstration

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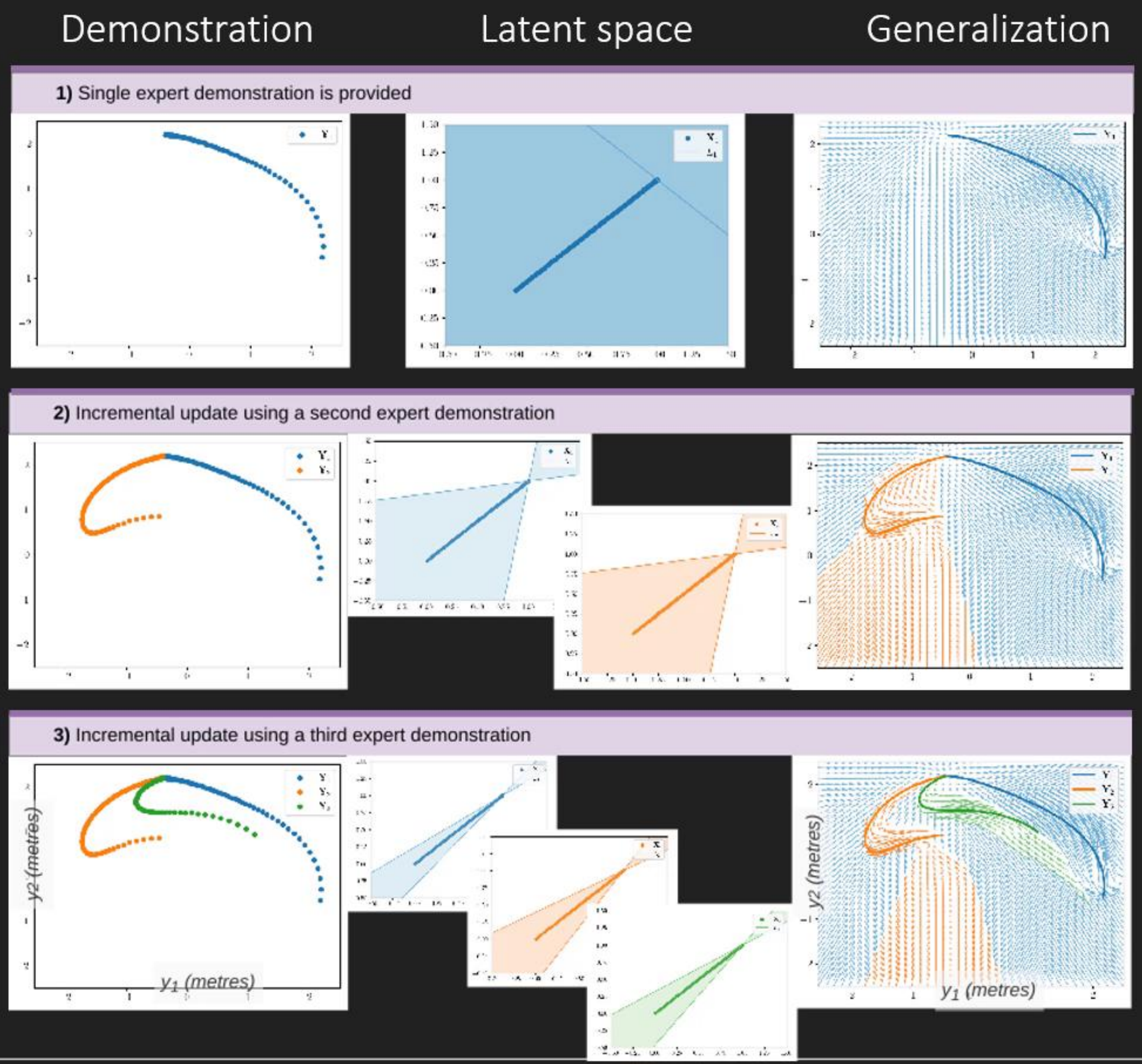


EPFL

Learning from demonstration

Transfer learning

Geometric algebra

Learning from demonstration:

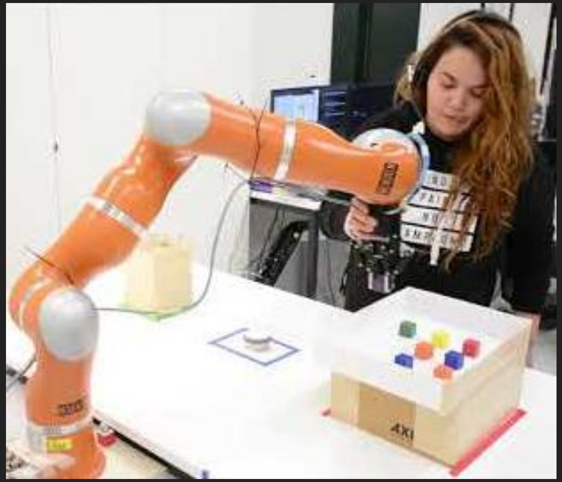
1. Developed a motion control strategy by using a Dynamical system.

Transfer learning:

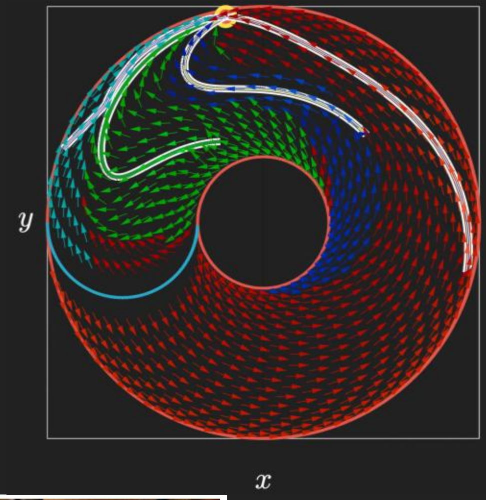
1. Investigating the efficiency of transferring a sub-domain to redundant robots.

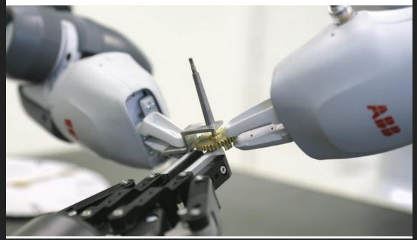
Conformal geometric algebra:

1. Necessary and sufficient conditions for a generic 3R robot to have four inverse kinematic solutions.



https://nbfigueroa.github.io





https://www.epfl.ch/labs/lasa/fr/sahr-fr/

Research activity: Summary

Journals (x 6) + 2 submitted

1: International Journal of Robotics Research (IJRR)
2, 3: Mechanism and Machine Theory (MMT)
4, 5, 6: RCIM, JMD, SI

Conferences (x 9) + 2 submitted

1. International Conference on Robotics and Automation (ICRA)
2. International Conference on Robotic Systems (IROS)

3 - 9 ISSAC, ARK, RAHA, AIR, CASE, CFM, RAAD

Invited Talks (x 4)

1. Summer school on Singularities (SIMERO)
2. RICAM Workshop on kinematics (RICAM WS5)
3. EPFL, Lausanne, Switzerland
4. ICube, Strasbourg, France

Book Chapter (x 1) + 1 submitted

1. Biologically inspired Series-Parallel Hybrid robots, Academic Press

Open source software

1. ParaOpt: Open source optimization tool for design of complex mechanisms.

Teaching and Supervision

1. 64 hours of TP, courses on design, kinematics and introduction to robotics
2. Supervised 4 Master’s student (currently +1)

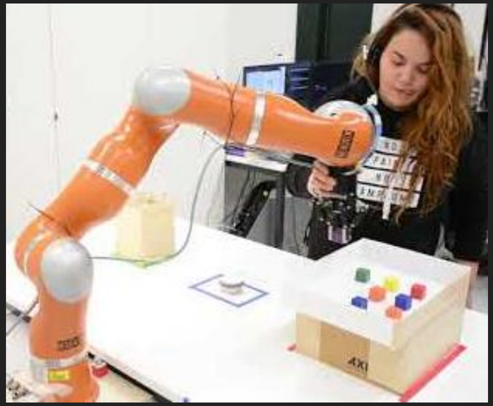
RESEARCH PROPOSAL

Current state of the art of learning from demonstration

Pignet et Calinon, 2019

http://users.eecs.northwestern.edu/~argall/learning.html

Argall et al. 2009



Ureche et Billard, 2015

Research proposal: Overall scheme (1/ 5)

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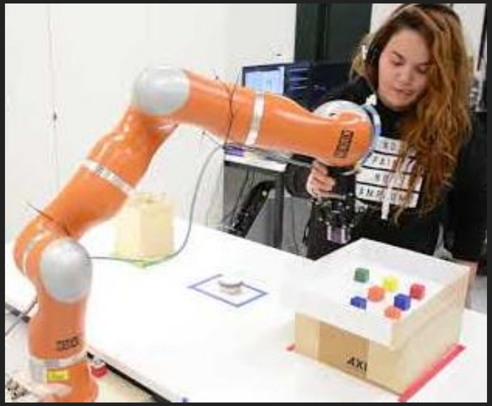


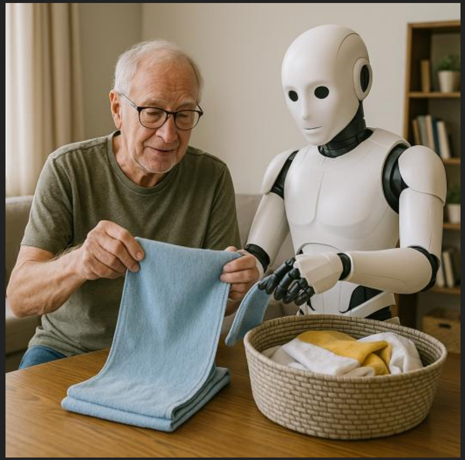
Ureche et Billard, 2015

1. Robots learn to perform tasks that are difficult to program.

2. The applications are still confined to highly controlled environments (such as specific mockups or laboratory experiments)

Research proposal: Overall scheme (2/ 5)

The future of learning from demonstration



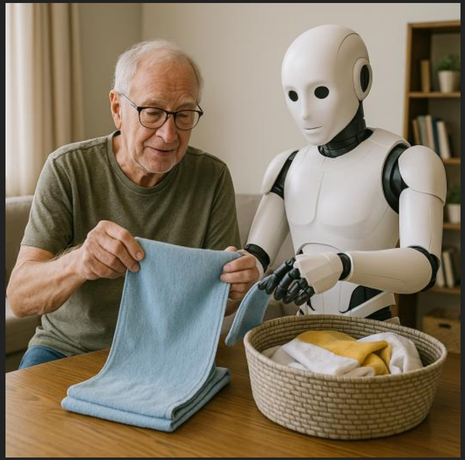
Robots learning from demonstration and share workspace with humans

Robots learn a behavior to work as an assistant in risk-critical applications

Images produced by ChatGpt

Research proposal: Overall scheme (2/ 5)

The future of learning from demonstration



Robots learning from demonstration and share workspace with humans

Robots learn a behavior to work as an assistant in risk-critical applications

1. Robots learn from demonstration in an unstructured environment.

2. The learned behavior can be generalized to different applications.

Images produced by ChatGpt

Research proposal: Overall scheme (3/ 5)

Challenges ahead:

1. Lack of understanding of global kinematic properties.

Research proposal: Overall scheme (3/ 5)

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1. Lack of understanding of global kinematic properties.

2. Task-specific motion planning, which is hard to generalize
   (Kober et al., 2010, Khansari et al., 2012)

Research proposal: Overall scheme (3/ 5)

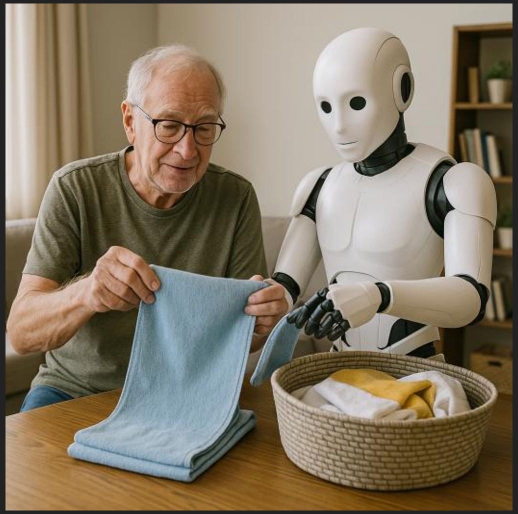
Challenges ahead:

1. Lack of understanding of global kinematic properties.

2. Task-specific motion planning, which is hard to generalize (Kober et al., 2010, Khansari et al., 2012)

3. Existing probabilistic models cannot provide guarantees or deterministic behavior (Nair et al., 2018)

Research proposal: Overall scheme (4/ 5)



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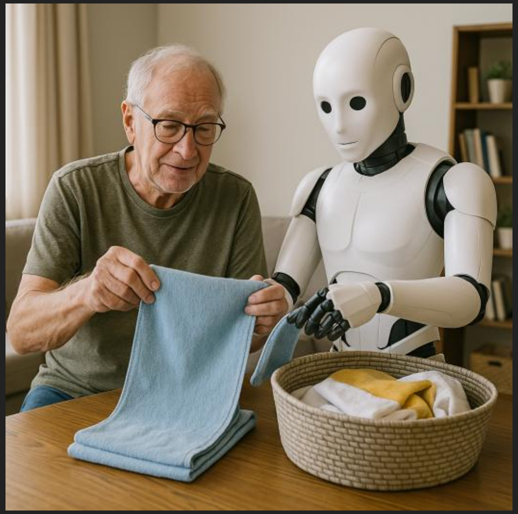
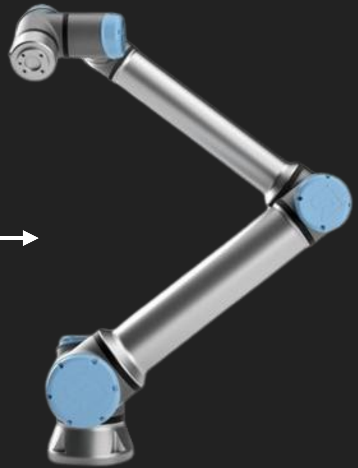
Research proposal: Overall scheme (4/ 5)

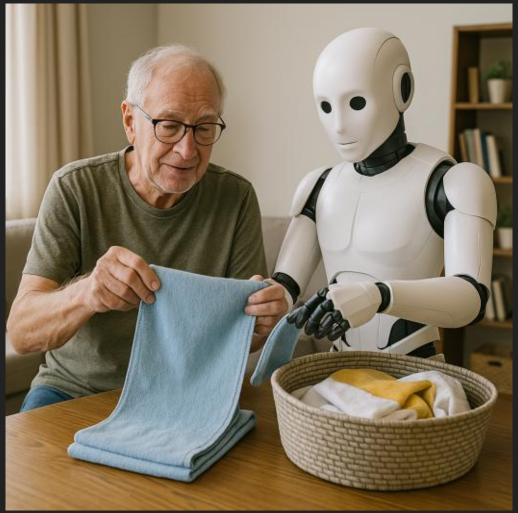


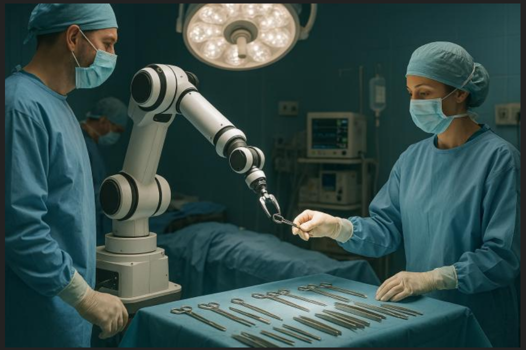


Industrial robot UR5
(noncuspidal)

Images produced by ChatGpt

Research proposal: Overall scheme (4/ 5)





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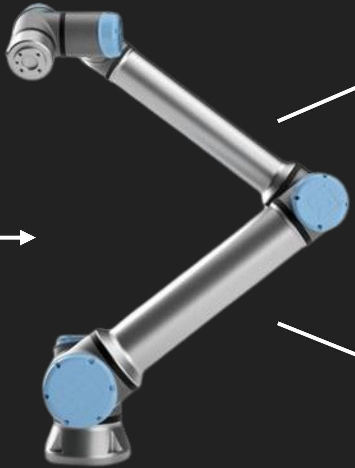


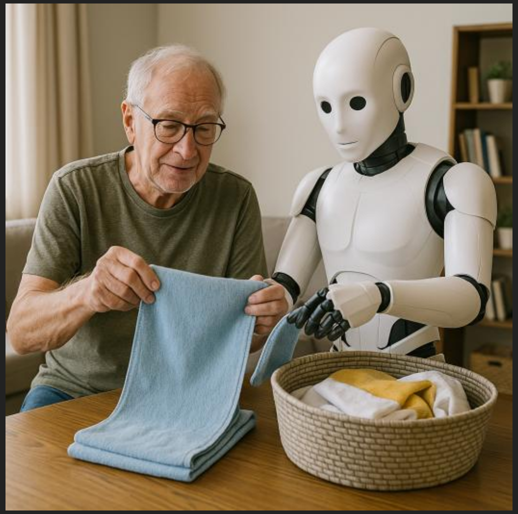
Industrial robot UR5 (noncuspidal)

Robot assistant Jaco Gen2 (cuspidal)

Cobot Fanuc CRX-10ia/L (cuspidal)

Research proposal: Overall scheme (4/ 5)

How can we
leverage kinematic properties
to robustly
learn from human demonstration
and transfer the behavior
to other robots?



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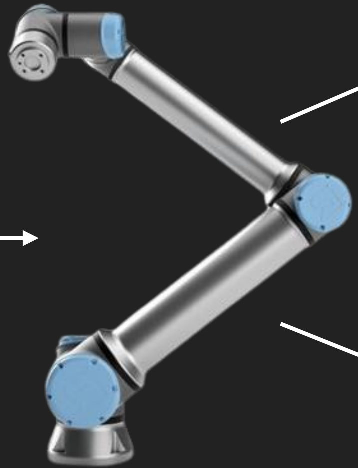

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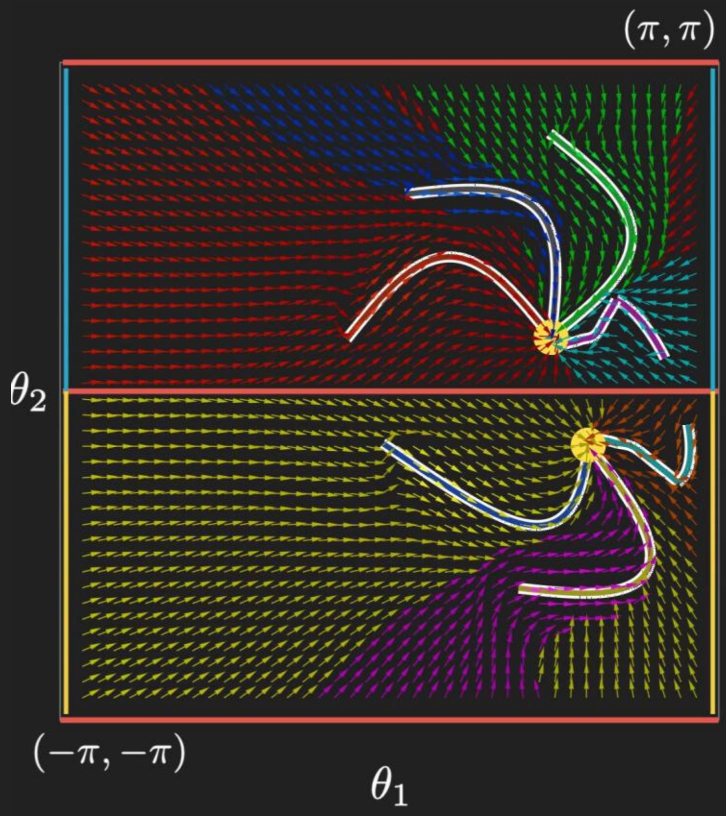
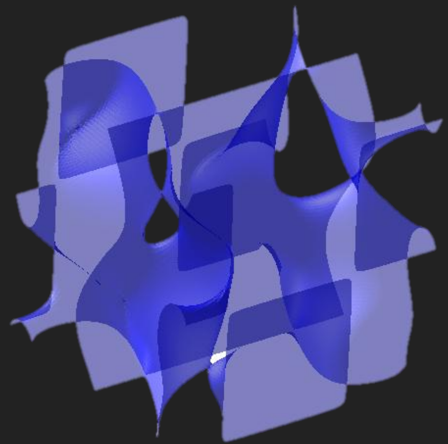
Research proposal: Overall scheme (5/ 5)

Axis 1:
Behavior generalization

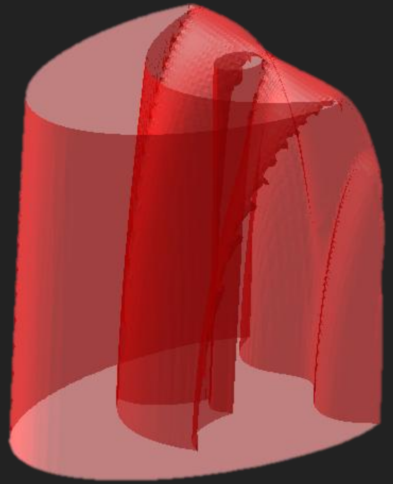


Demonstration in joint space

Axis 2:
Kinematic analysis



Joint space singularities



workspace singularities

Axis 3:
Transfer learning

Noncuspidal
6R robot

Cuspidal 6R robot

Redundant 7R robot

Axis 1: Learning behaviour from demonstration

Short term — How can we generalize behavior that respects constraints?

Mid term — Which techniques can be used to have robust behavior?

Long term — How can complex behavior be produced in robots from multiple demonstrations?

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Mid term — Which techniques can be used to have robust behavior?

Long term — How can complex behavior be produced in robots from multiple demonstrations?

Axis 1: Learning behaviour from demonstration

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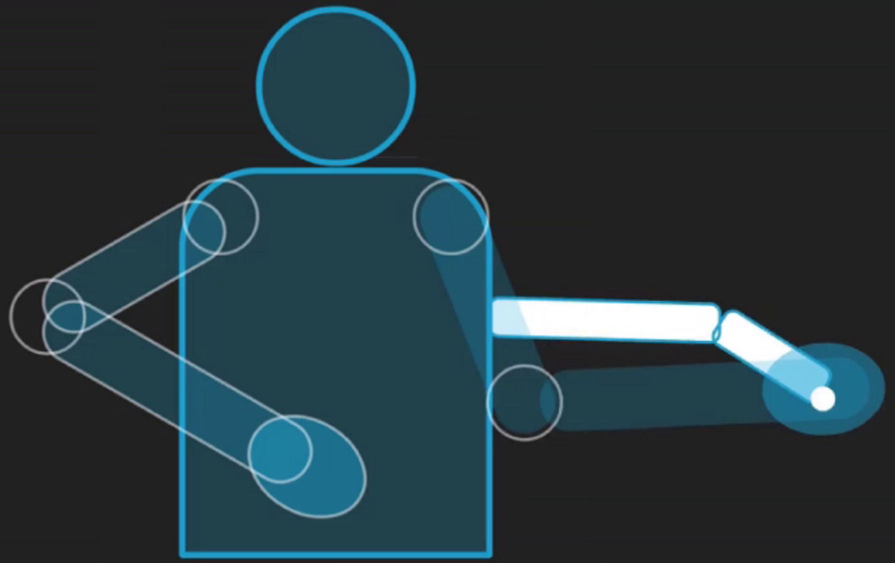
2. This leads to infeasible paths or unexpected behavior in task space.



Human demonstration

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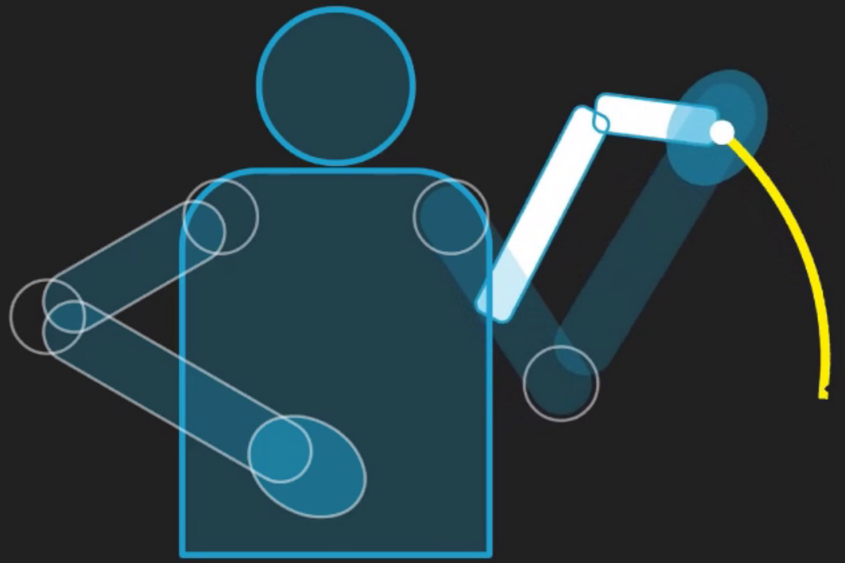

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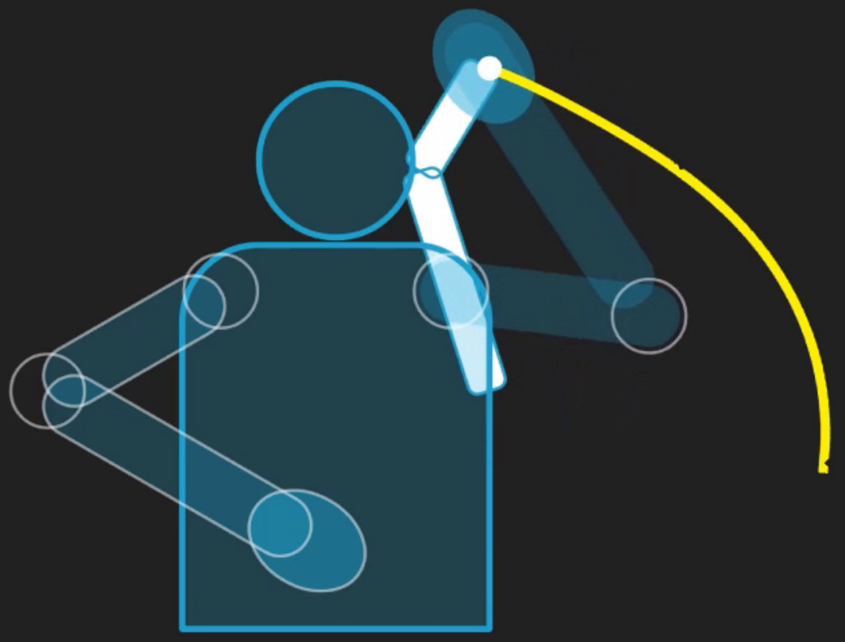

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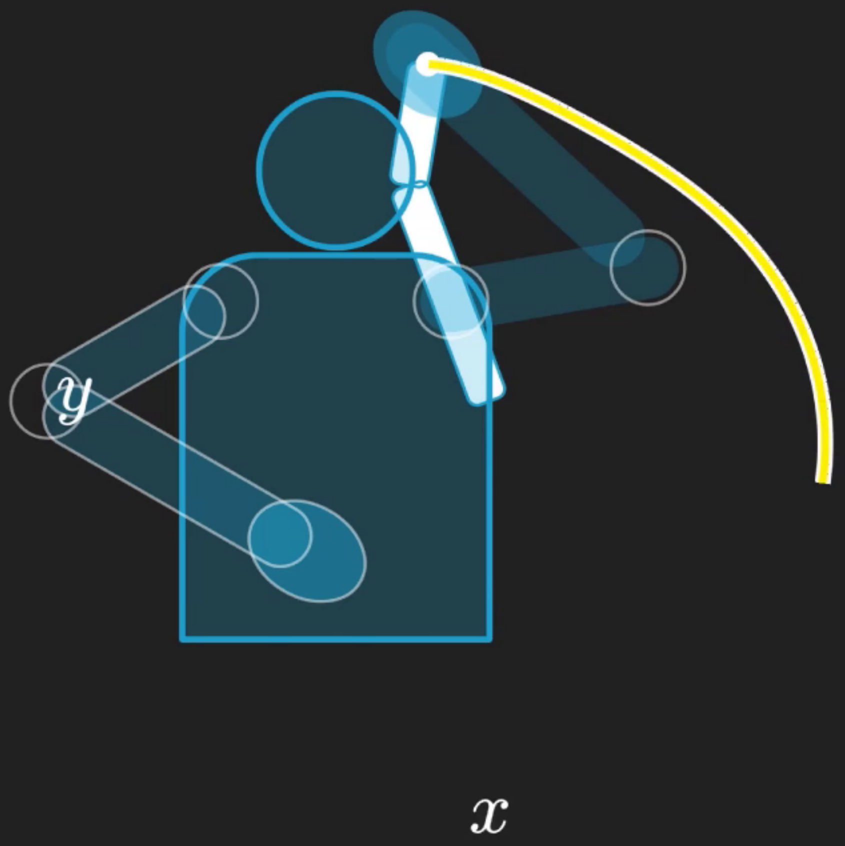

Human demonstration

Axis 1: Learning behaviour from demonstration

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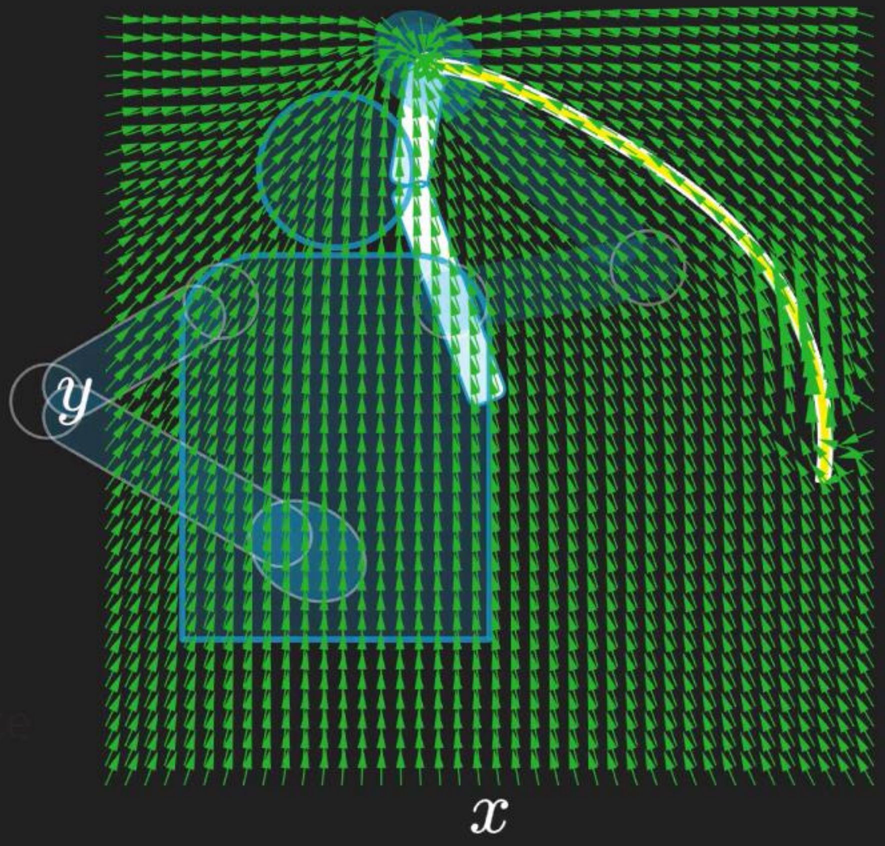
The motion vector field passes through singularities in the workspace



Generalized behaviour in workspace

Axis 1: Learning behaviour from demonstration

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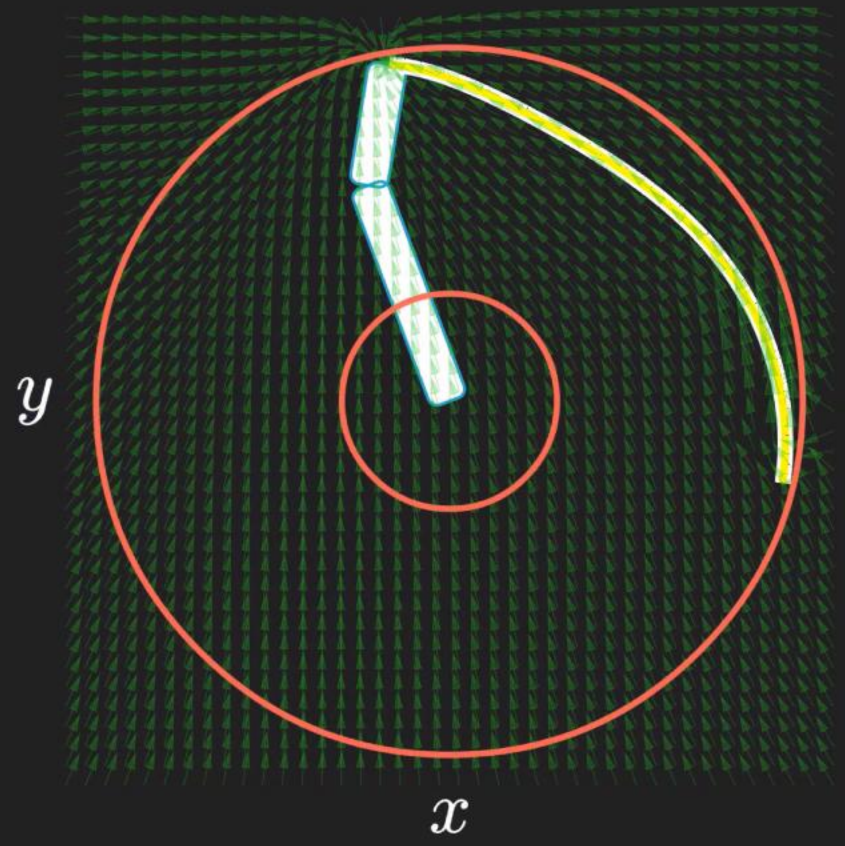

Generalized behaviour in workspace

Axis 1: Learning behaviour from demonstration

Motion planning in the workspace is preferred as the demonstration is performed in task space

1. The dynamical system generates motion without considering the space constraints.

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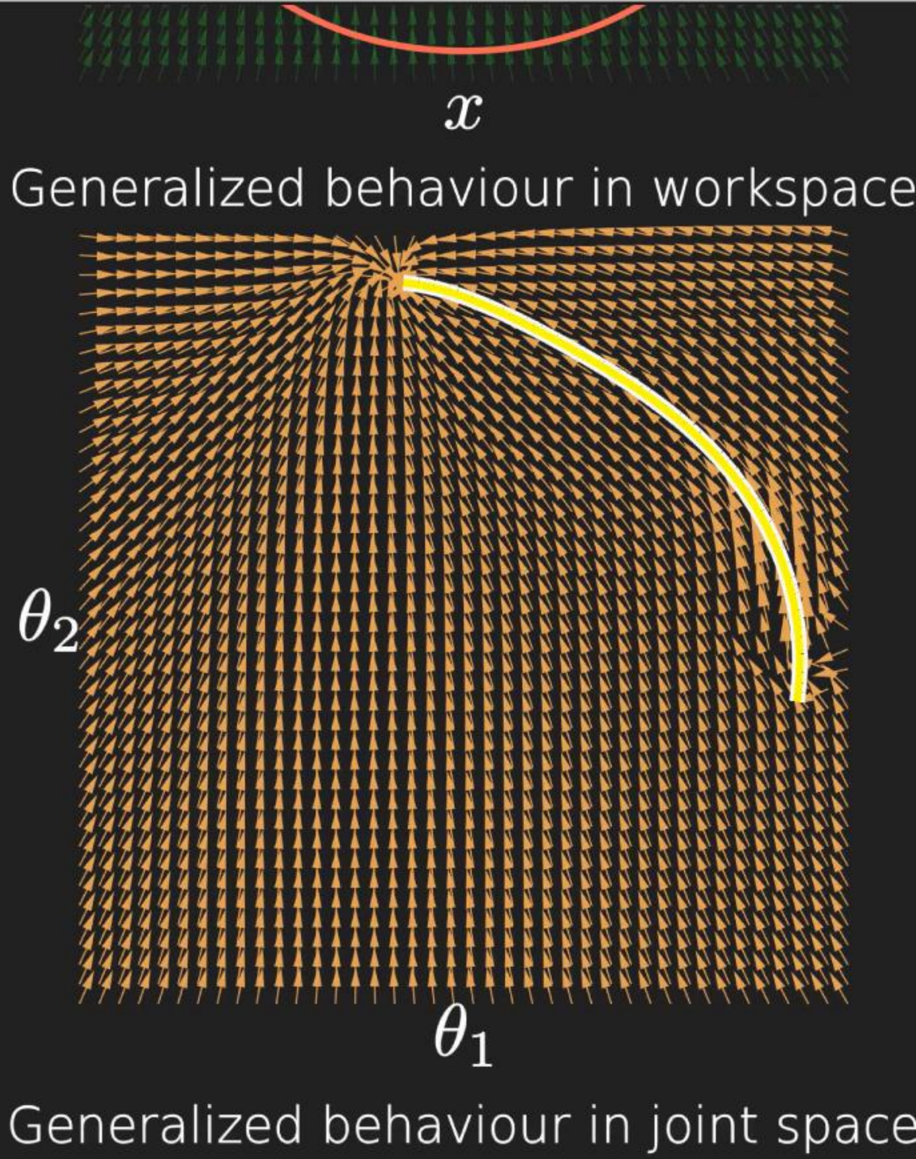
3. Similarly the singularities in joint space create issues like bounce back in the robot



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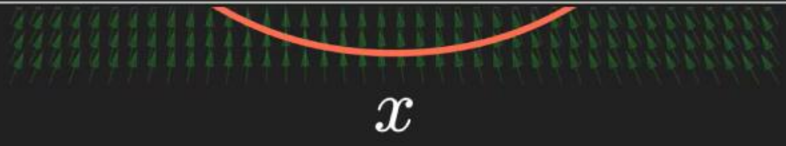

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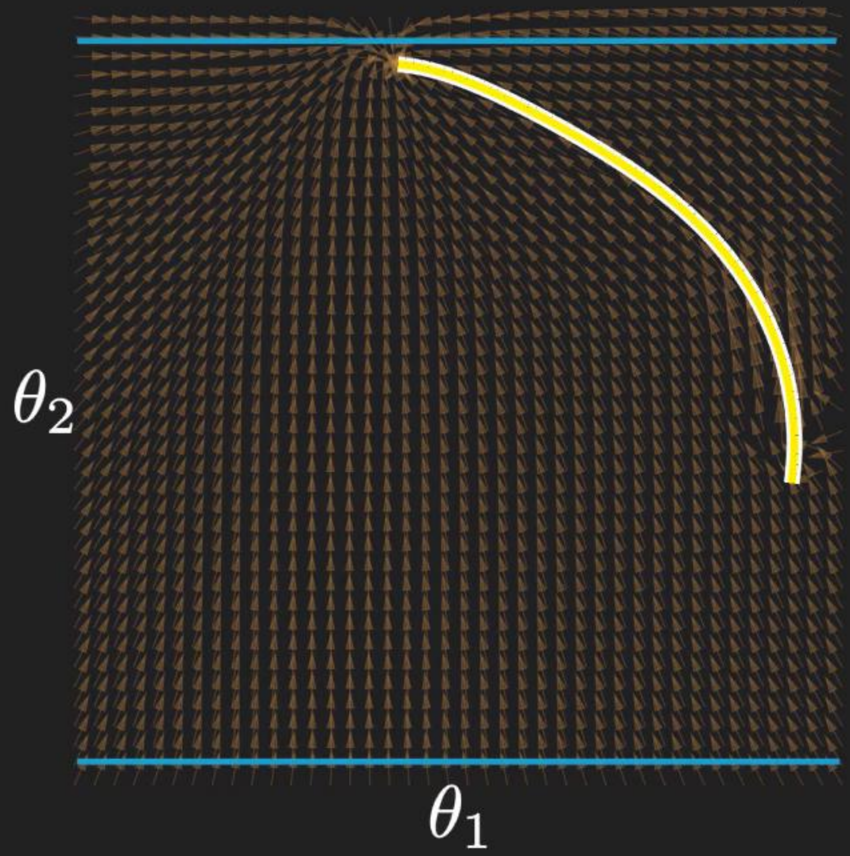

Generalized behaviour in joint space

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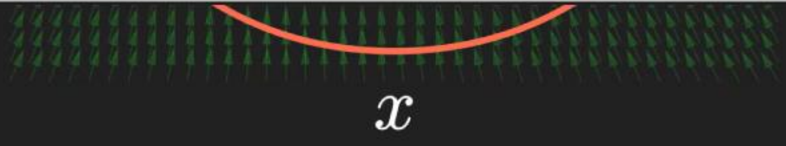
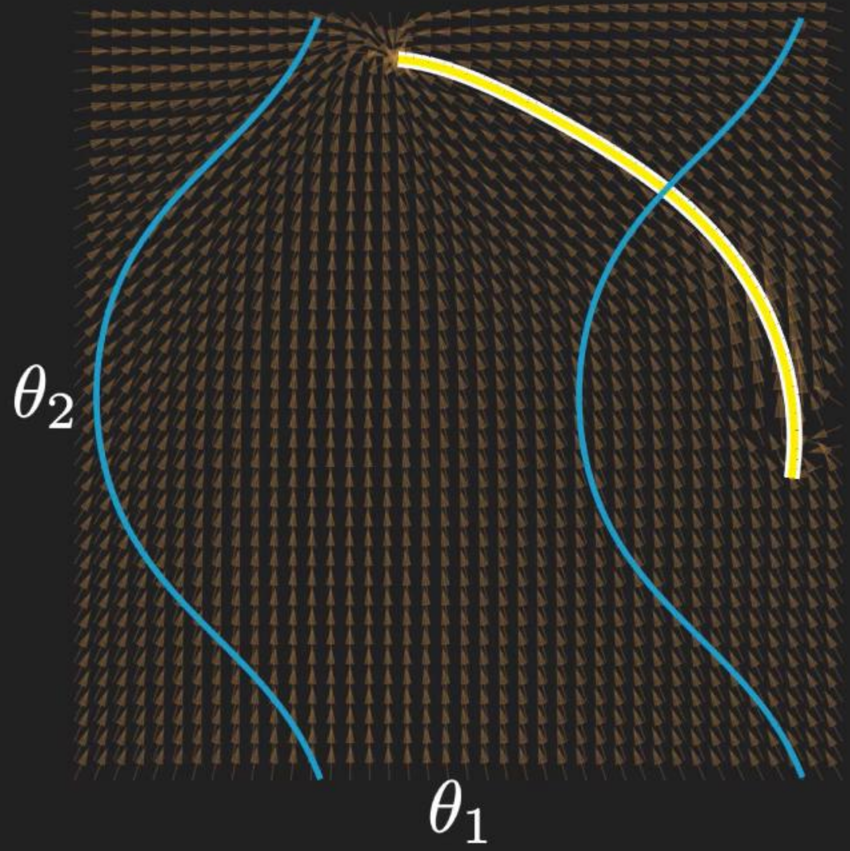


Generalized behaviour in workspace



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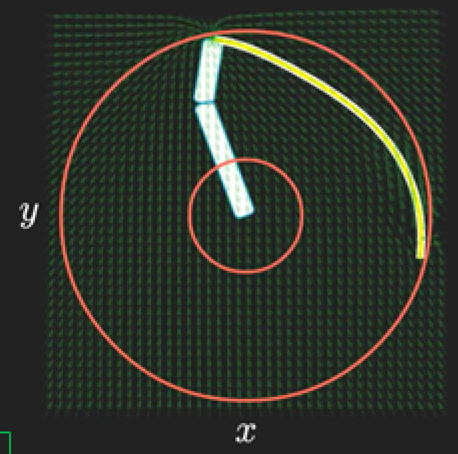
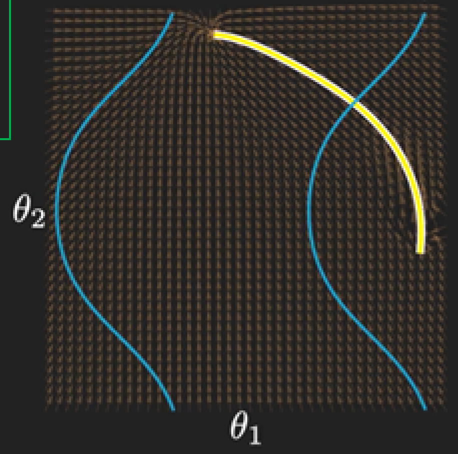
Learn behavior in joint space by exploring paths upon perturbation in workspace



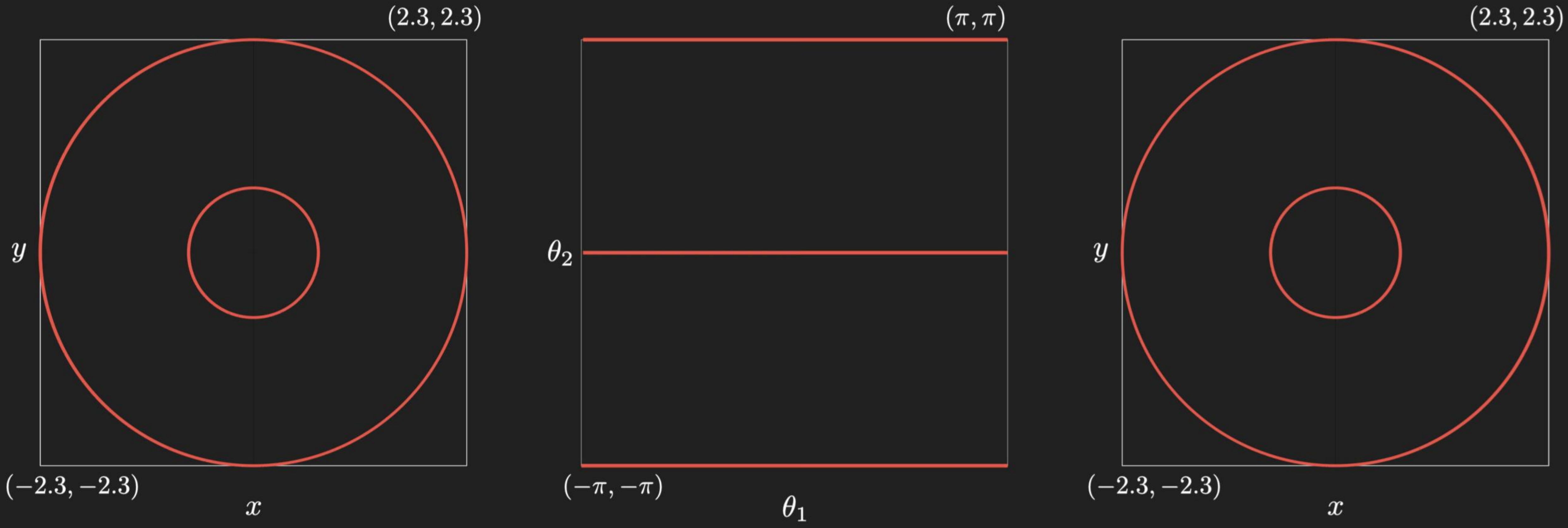
Generalized behaviour in workspace



Generalized behaviour in joint space

Axis 1: Learning behaviour from demonstration

Illustration of motion planning in joint space to respect space constraints



Singularities in work space

Singularities in joint space

Singularities in work space

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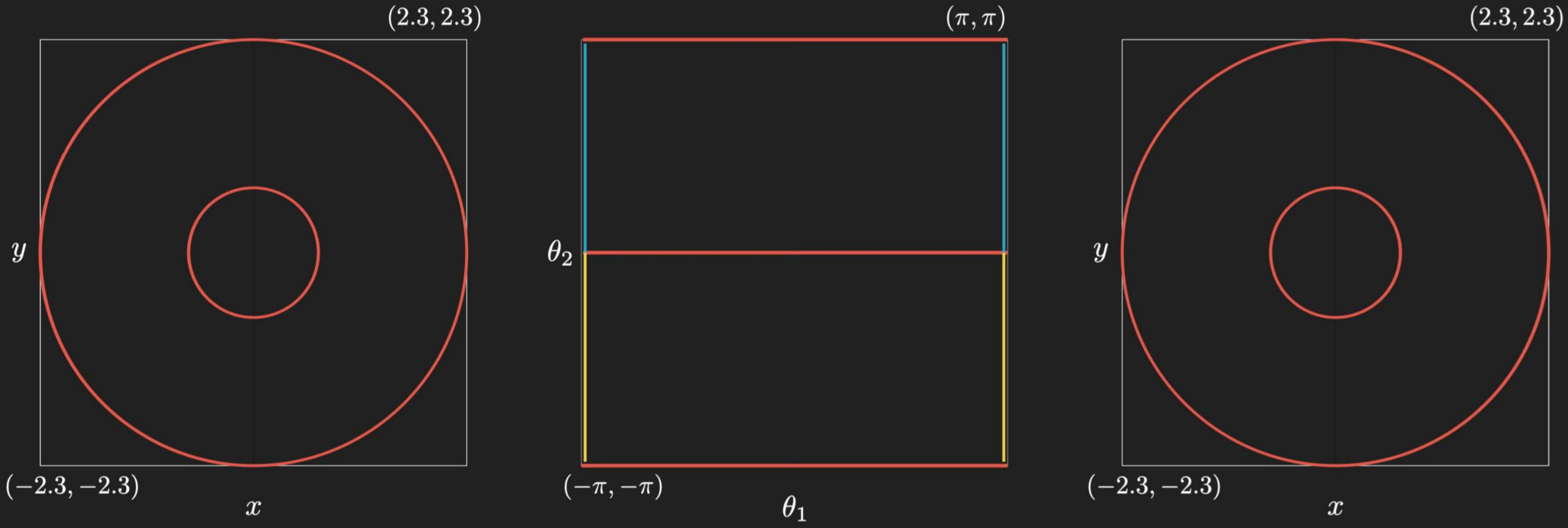

Joint limits in joint space

Axis 1: Learning behaviour from demonstration

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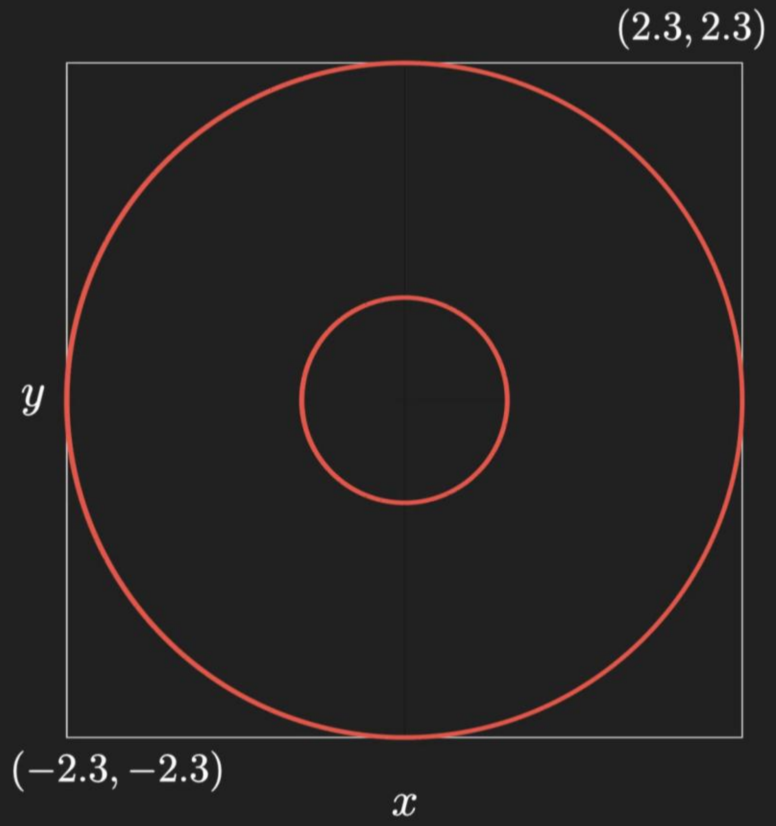

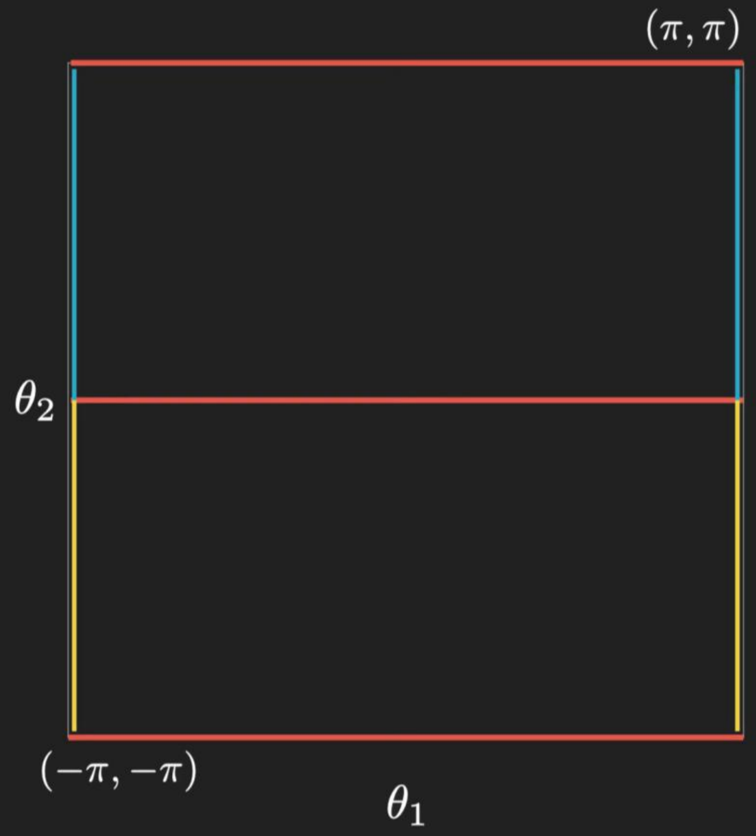

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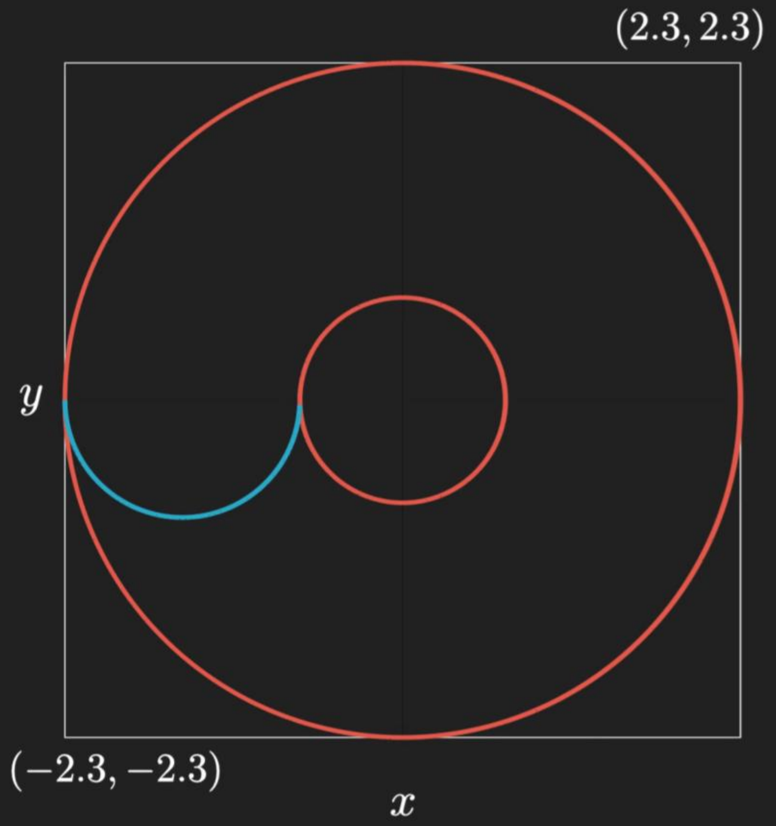

Joint limits in work space for aspect 1

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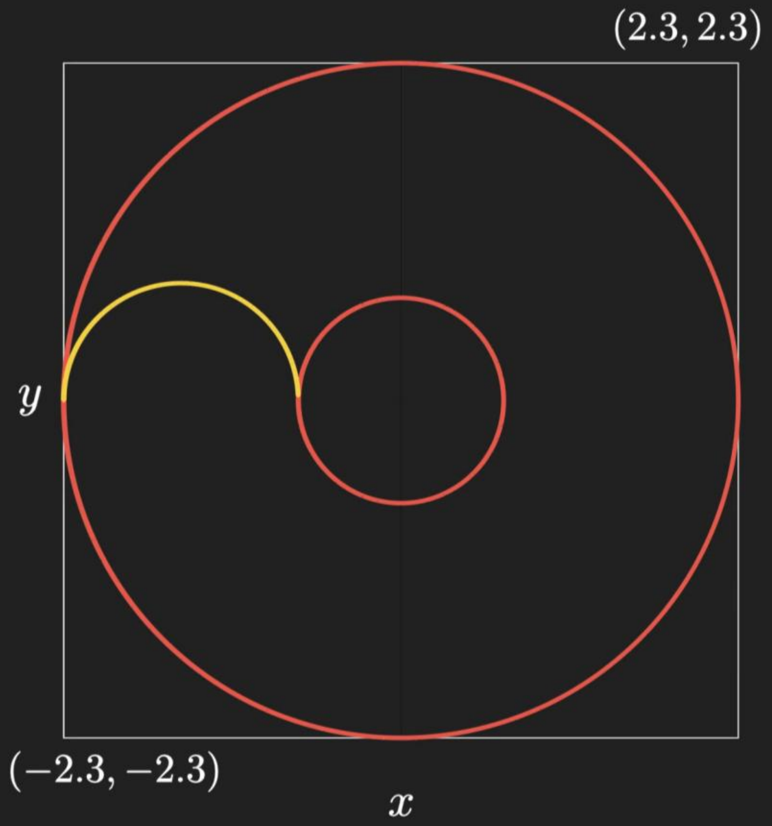
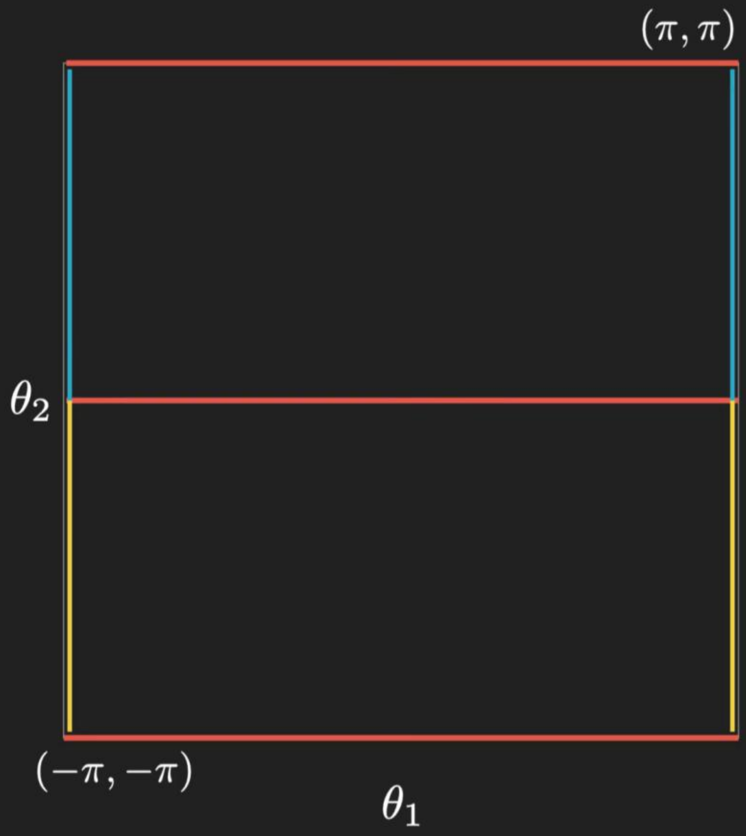
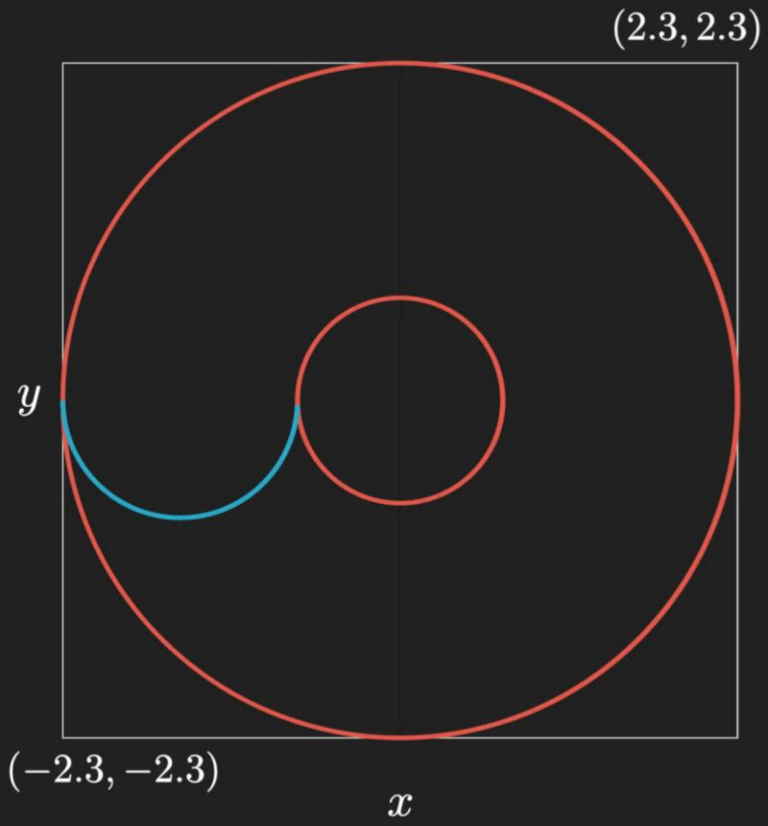


Joint limits in work space for aspect 2



Joint limits in joint space



Joint limits in work space for aspect 1

Axis 1: Learning behaviour from demonstration

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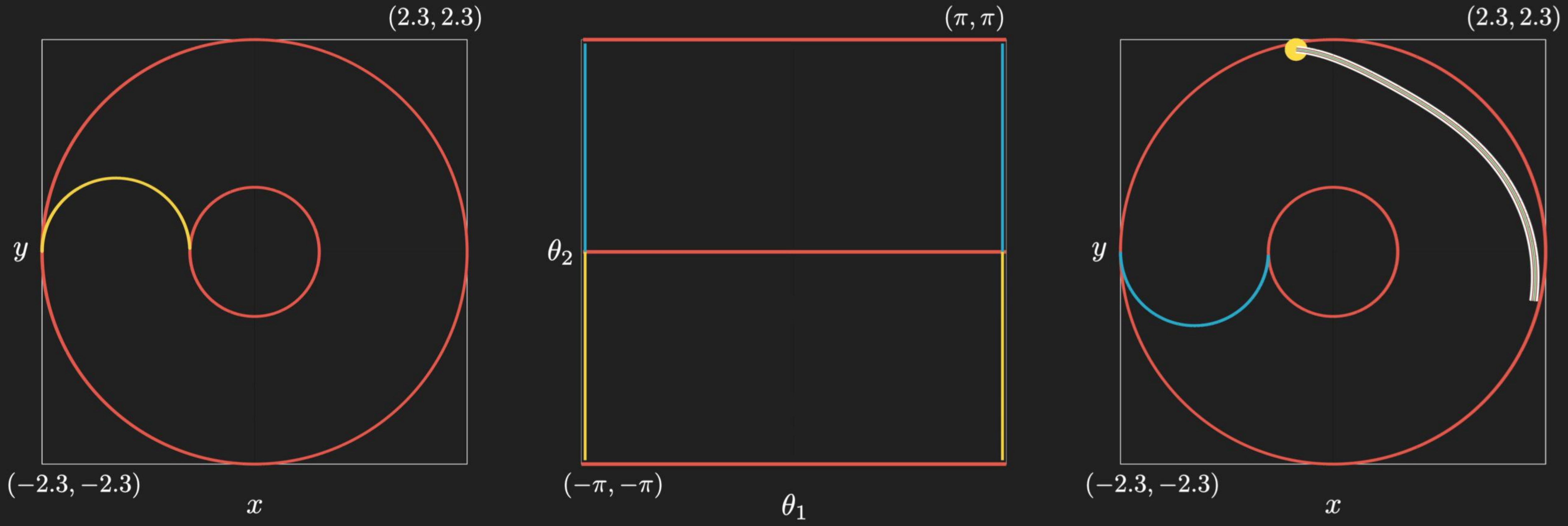

Demonstartion recorded in workspace

Axis 1: Learning behaviour from demonstration

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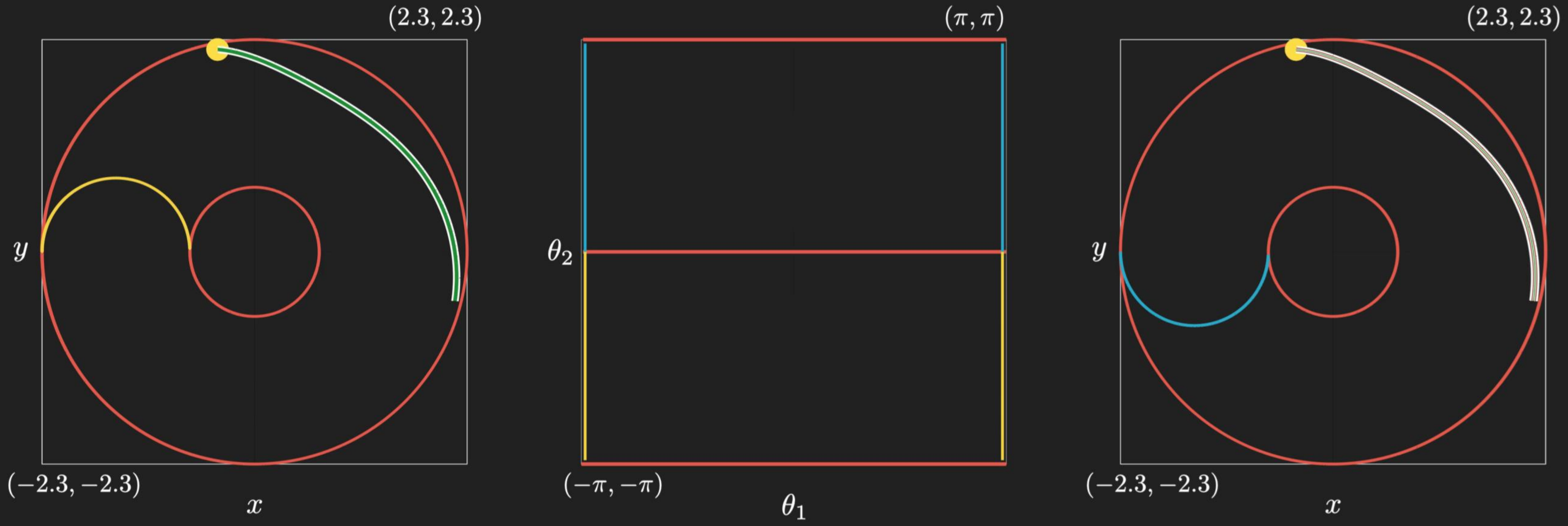
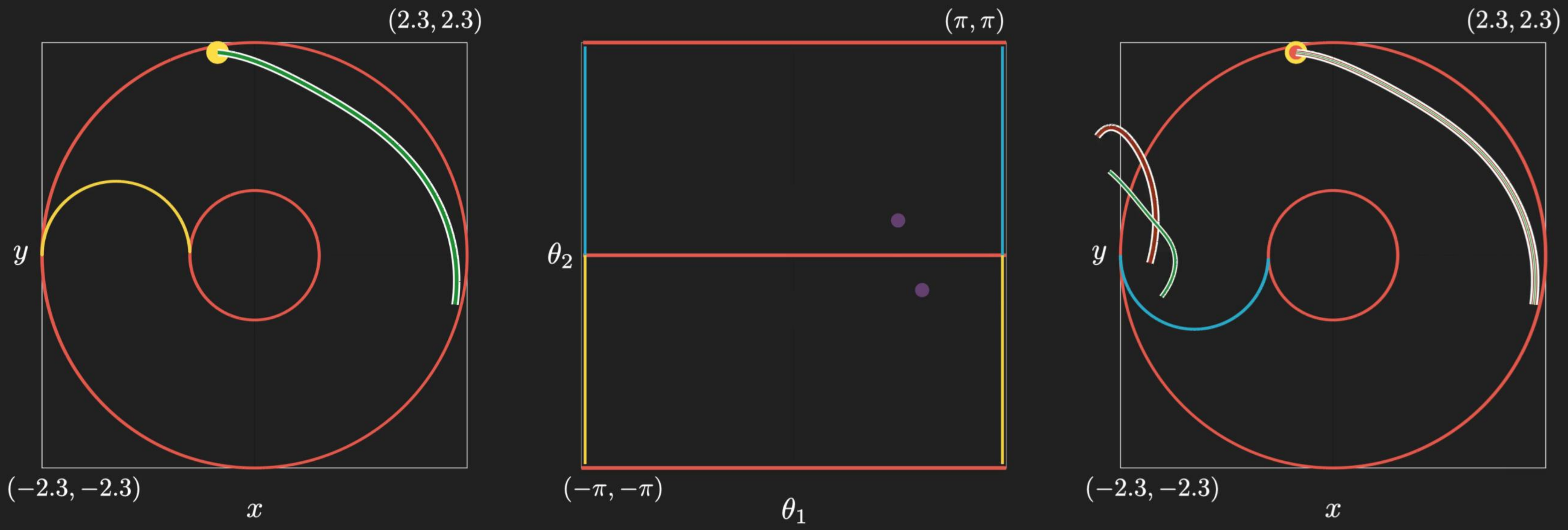


Demonstartion recorded in workspace for aspect 2

Demonstartion recorded in workspace

Axis 1: Learning behaviour from demonstration

Illustration of motion planning in joint space to respect space constraints



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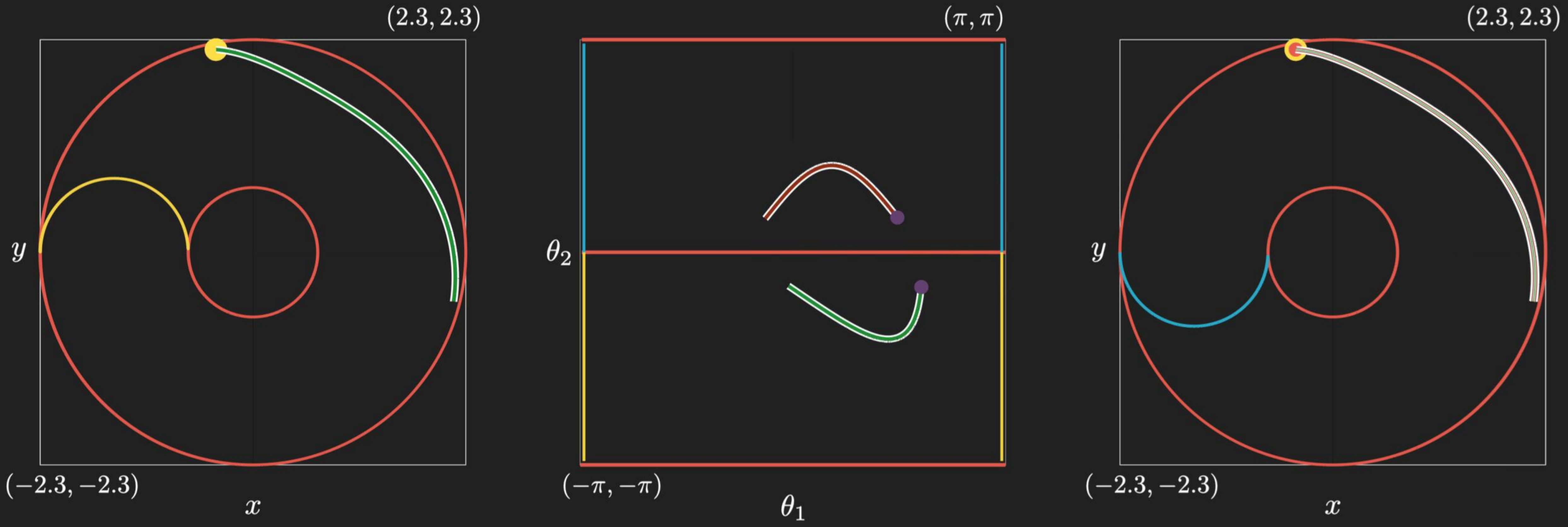

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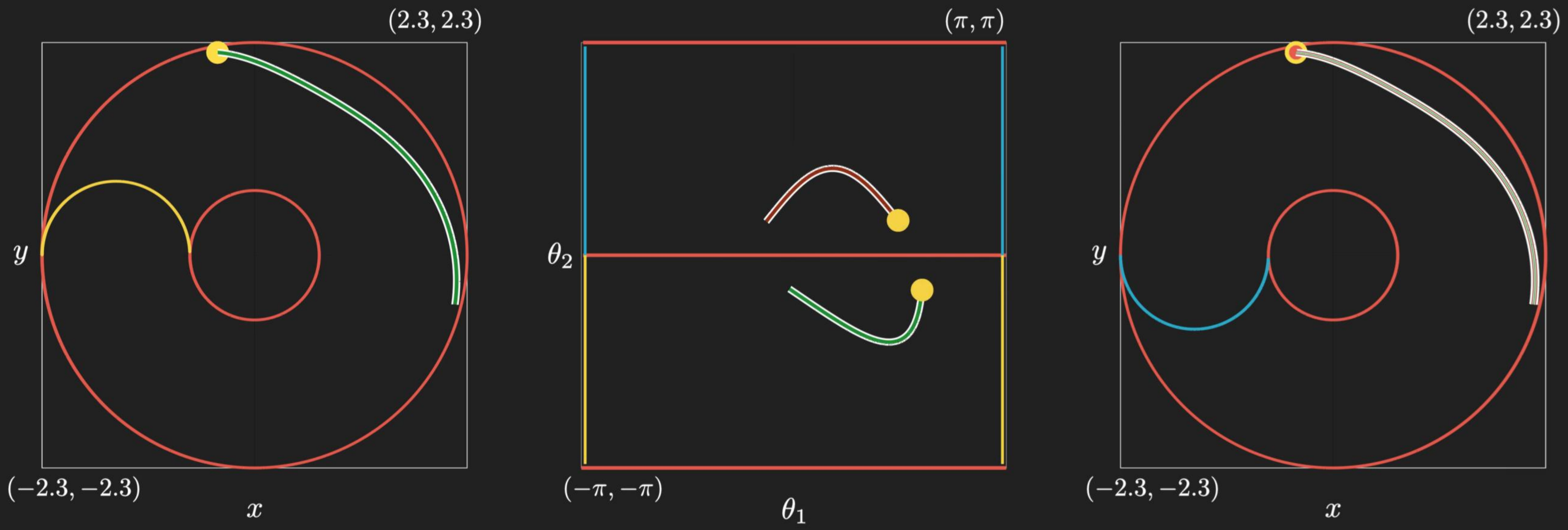
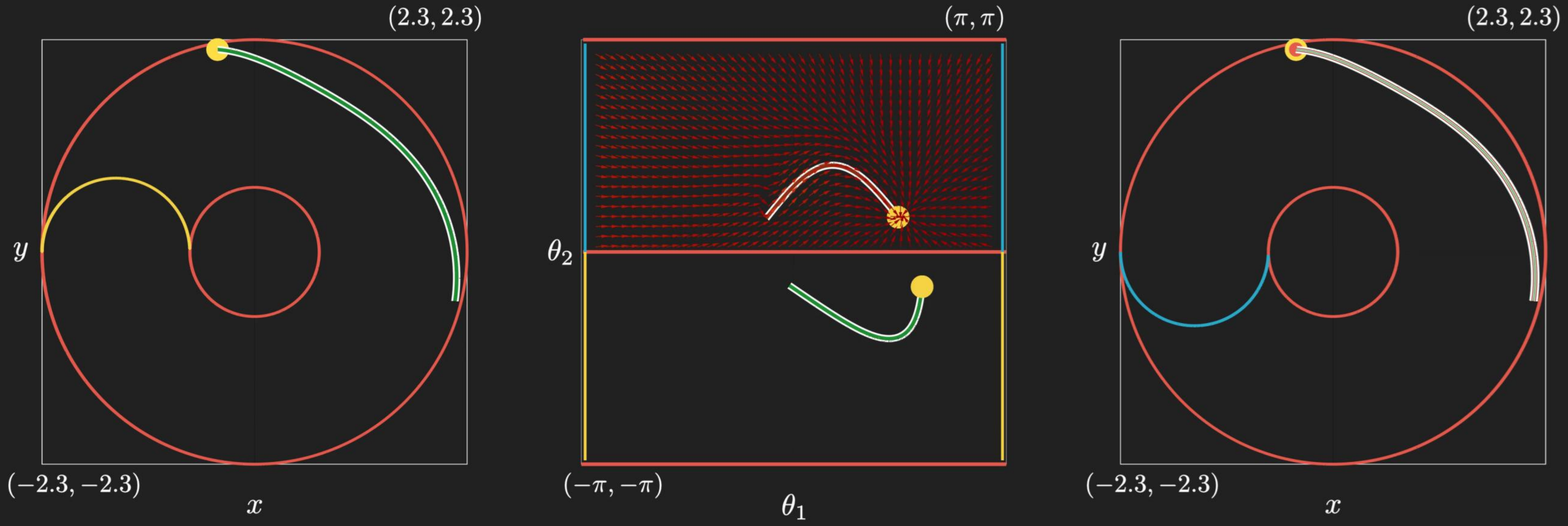


Demonstration in joint space

Generalization in joint space

Axis 1: Learning behaviour from demonstration

Illustration of motion planning in joint space to respect space constraints



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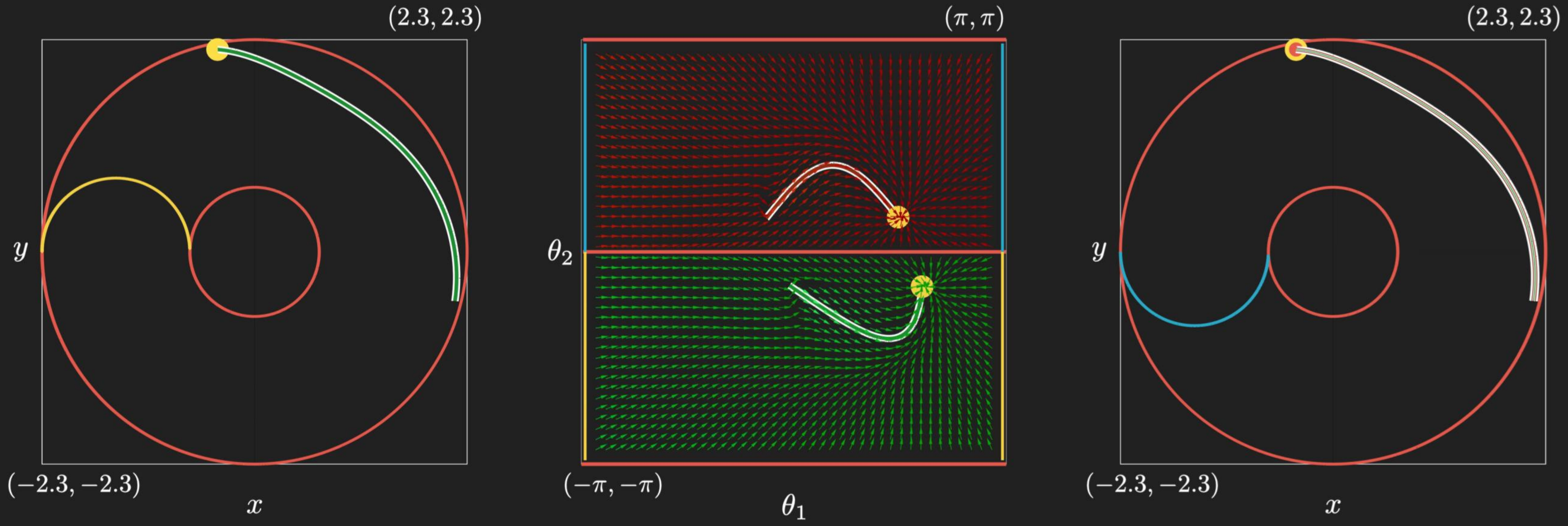

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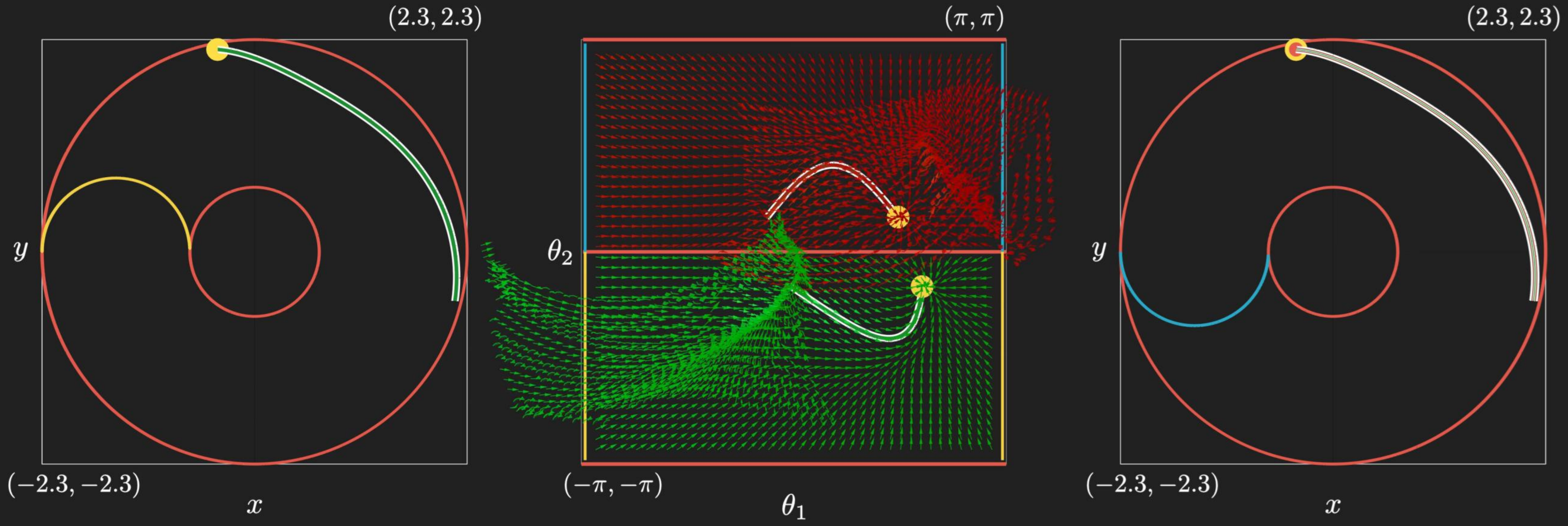

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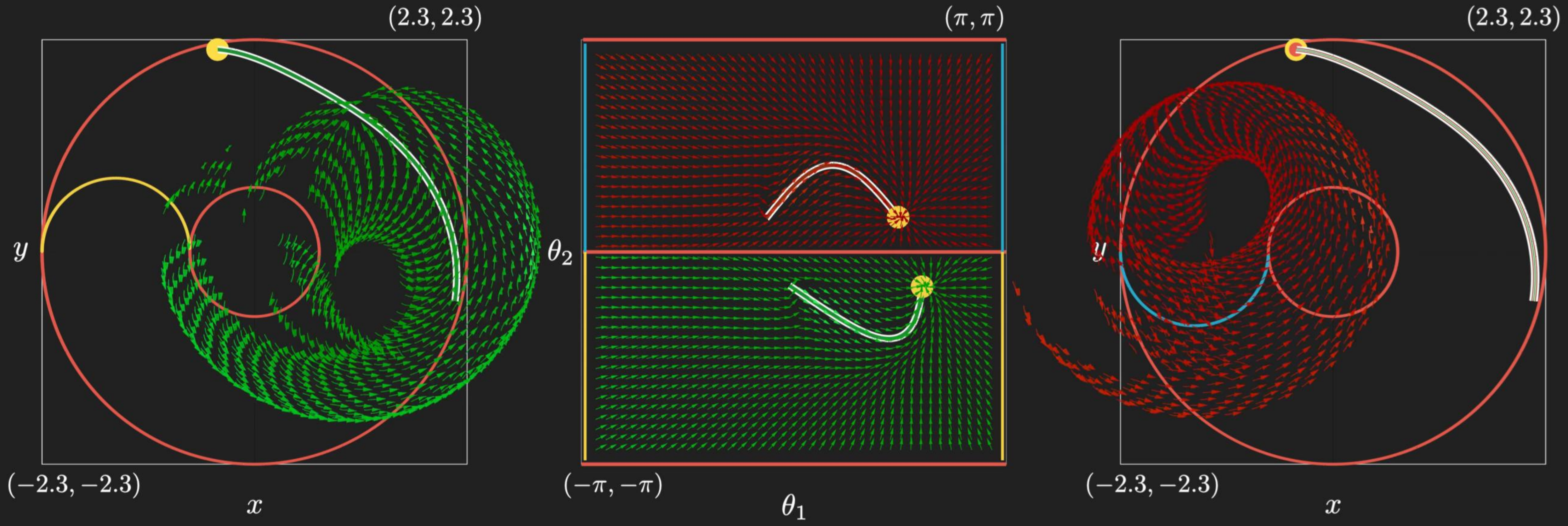

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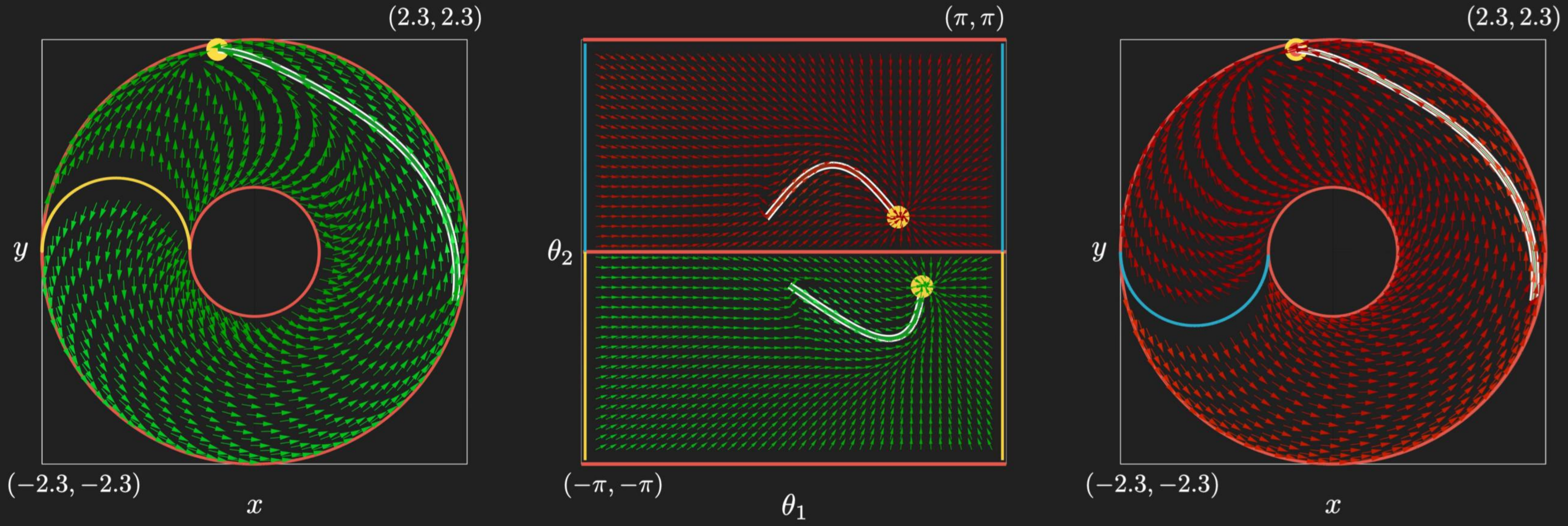

Demonstration in joint space

Generalization in joint space

Axis 2: Kinematic analysis

Short term	How can we classify robot singularities for the transfer of behavior?
Short term	Study on the singularities of generic 7R robots
Mid term	Certified motion planning that considers obstacle avoidance
Long term	Bring geometric insights into generic 6R, 7R robots and robots with `X’-joints

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Axis 2: Kinematic analysis

7R robots are widely used for learning from demonstration

https://www.robots.com/articles/the-collaborative-kuka-lbr-iiwa-series-aka-your-third-hand

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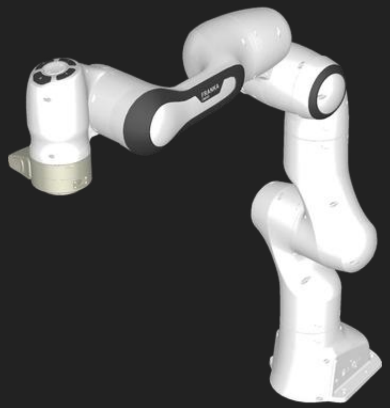

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Pignet et Calinon, 2019

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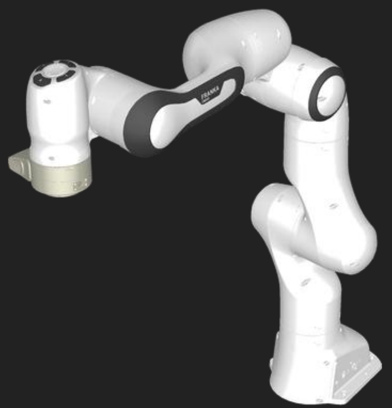

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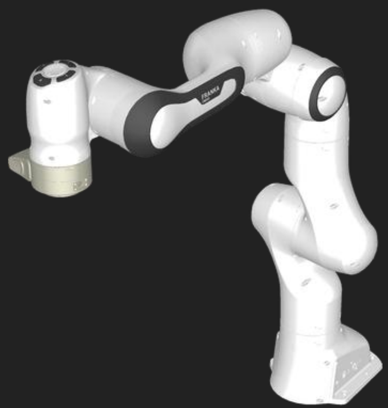
Pignet et Calinon, 2019

Hes-so: LD4Robots - Learning from Demonstration for Collaborative Robot

Axis 2: Kinematic analysis

7R robots are widely used for learning from demonstration

Simplified kinematics



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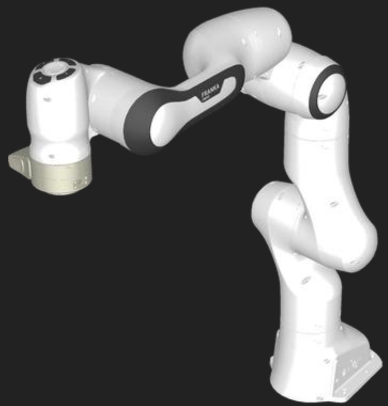

More
complex

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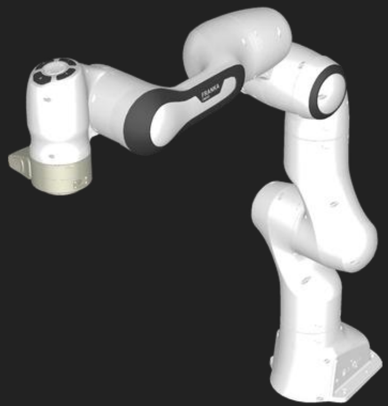

More complex

Hard
(Asgari et al. 2025)

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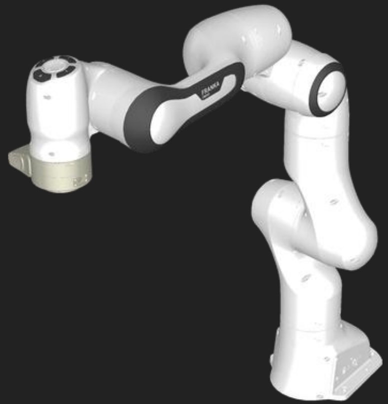

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Singularity analysis is hard due to the limitations of current mathematical tools used in robotics

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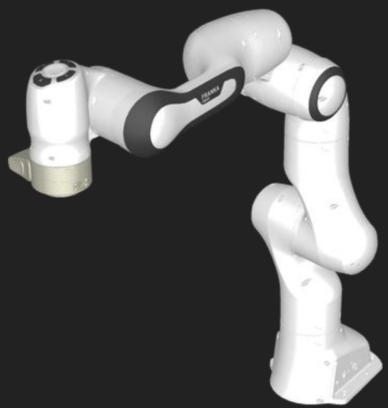

More complex

Hard (Asgari et al. 2025)

Singularity analysis is hard due to the limitations of current mathematical tools used in robotics

Reduce dimension to simplify analysis
+
gain geometric insight by using modern tools such as Conformal Geometric Algebra

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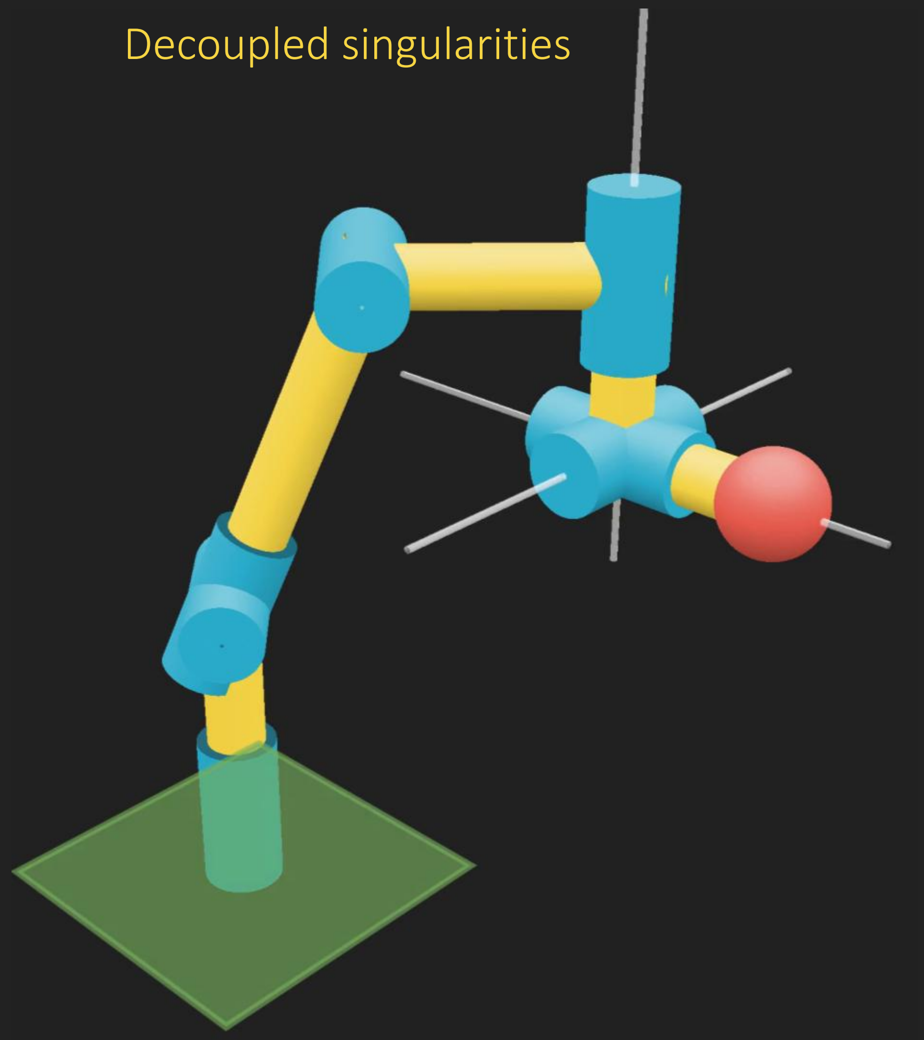
Pignet et Calinon, 2019

Hes-so: LD4Robots - Learning from Demonstration for Collaborative Robot

Axis 2: Kinematic analysis

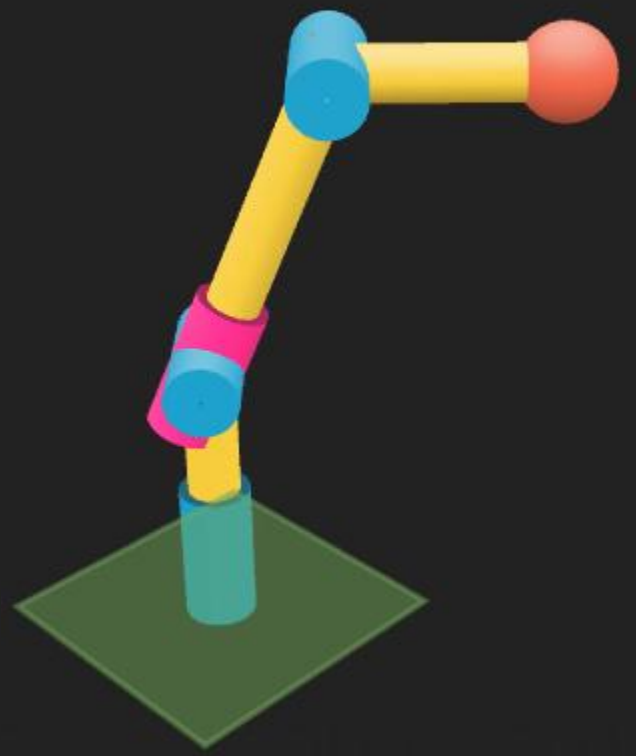
4R positional robot + 3R orientation wrist

Decoupled singularities



4R robot => 3R positional robot+ 1 parameter

Visualizable singularities!



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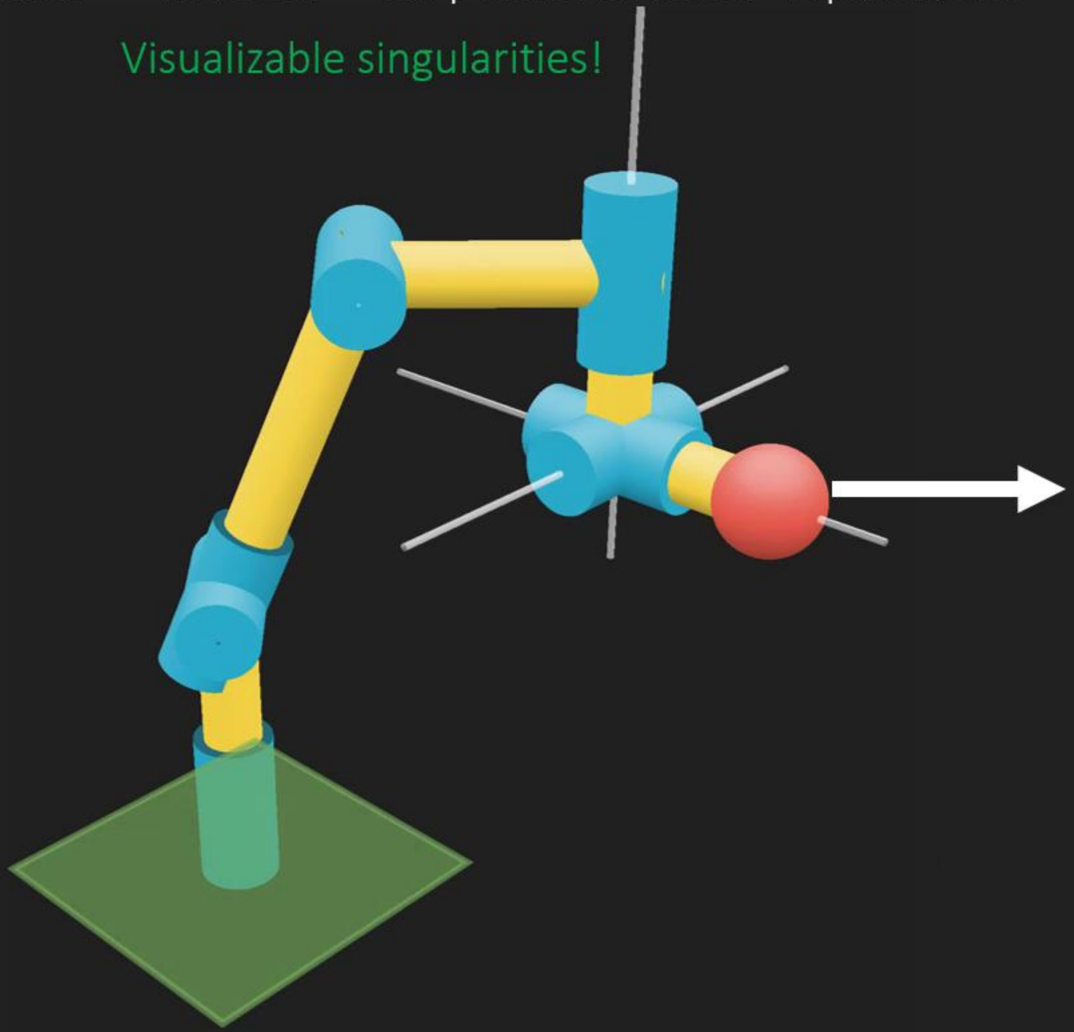
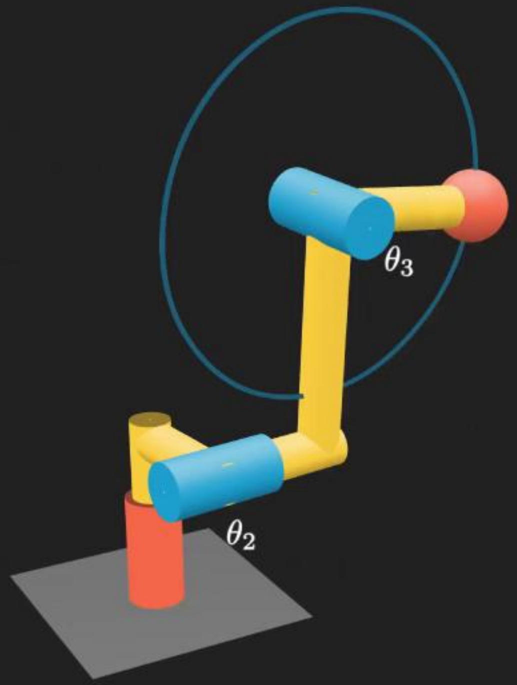


3R positional robot => reduced to only 2 parameters

Singularities plot in 2D plane



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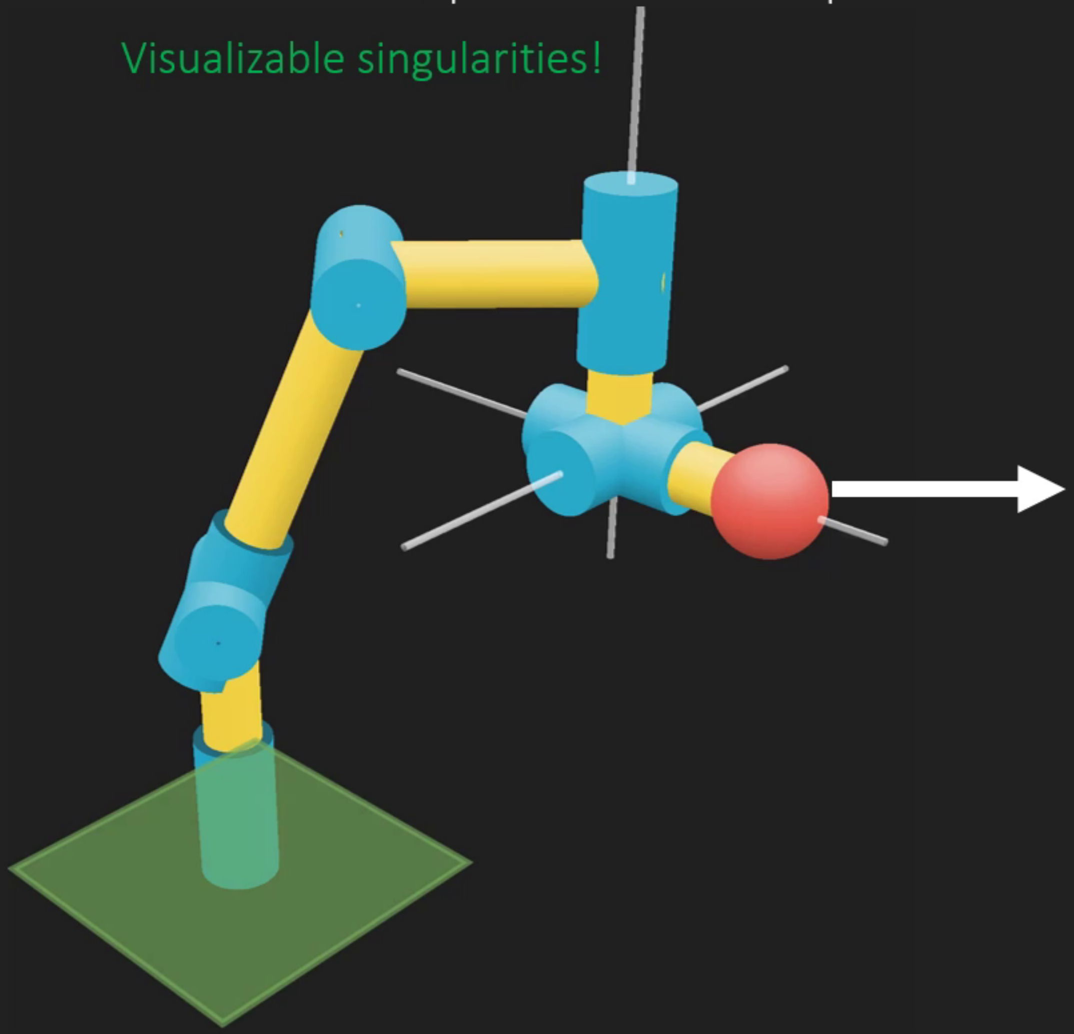

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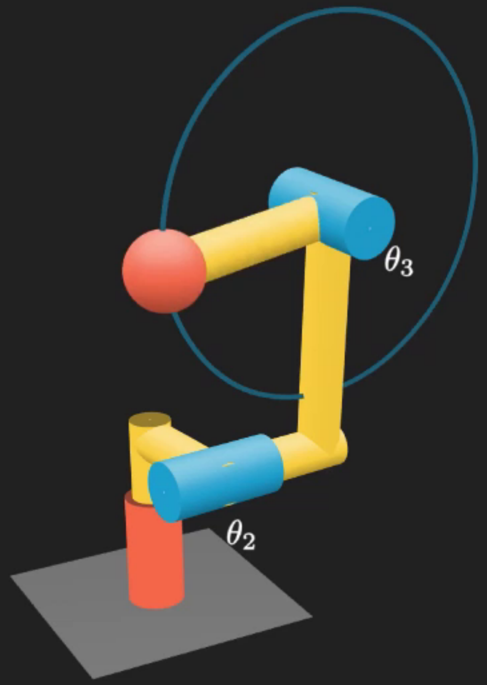

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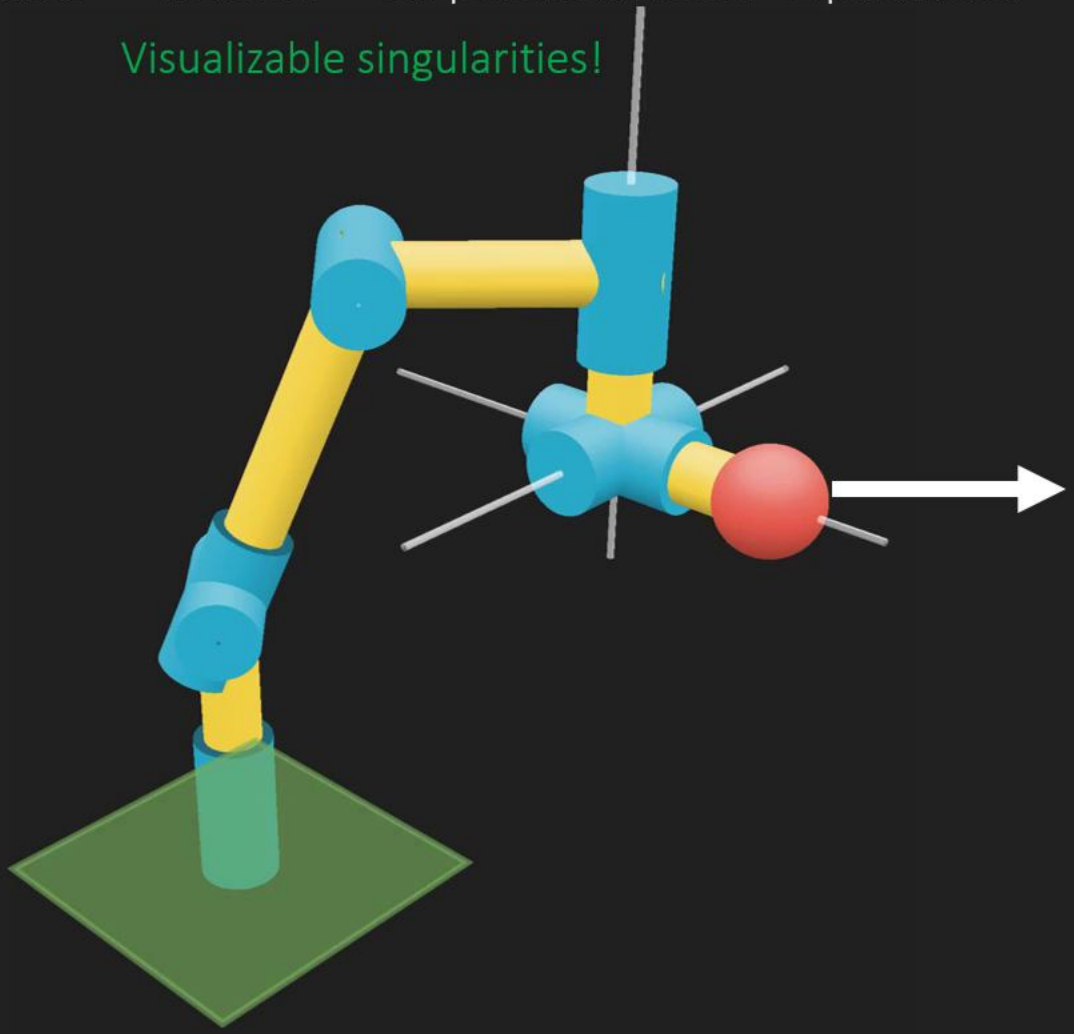

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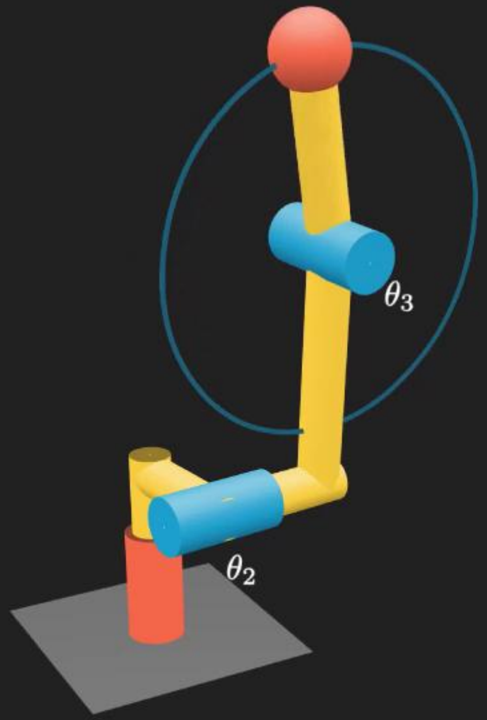

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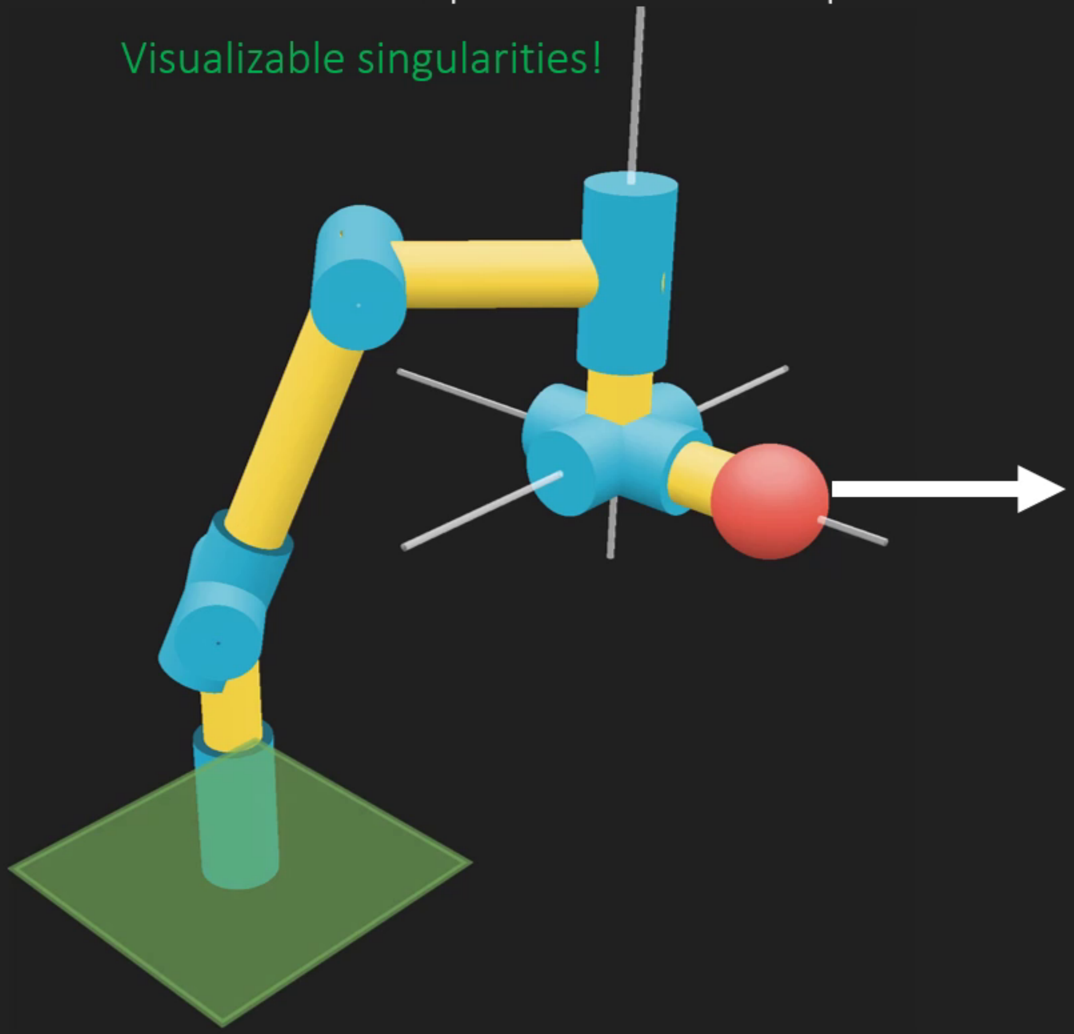

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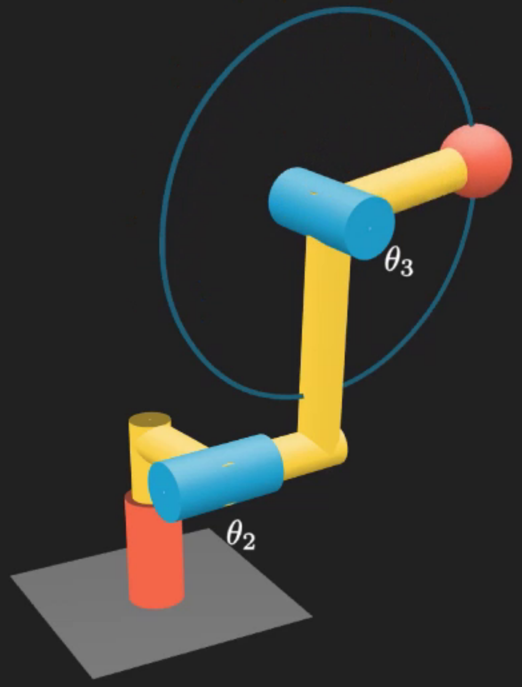

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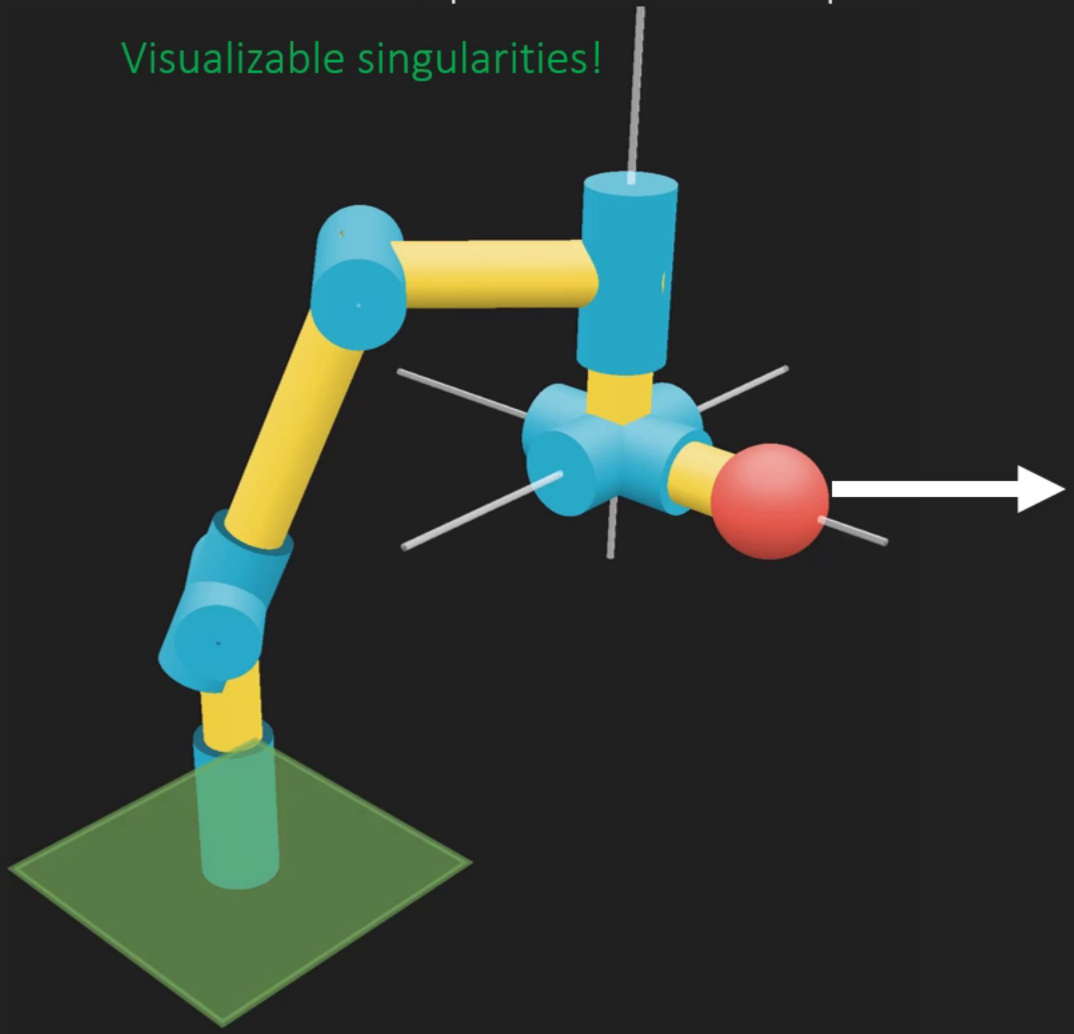

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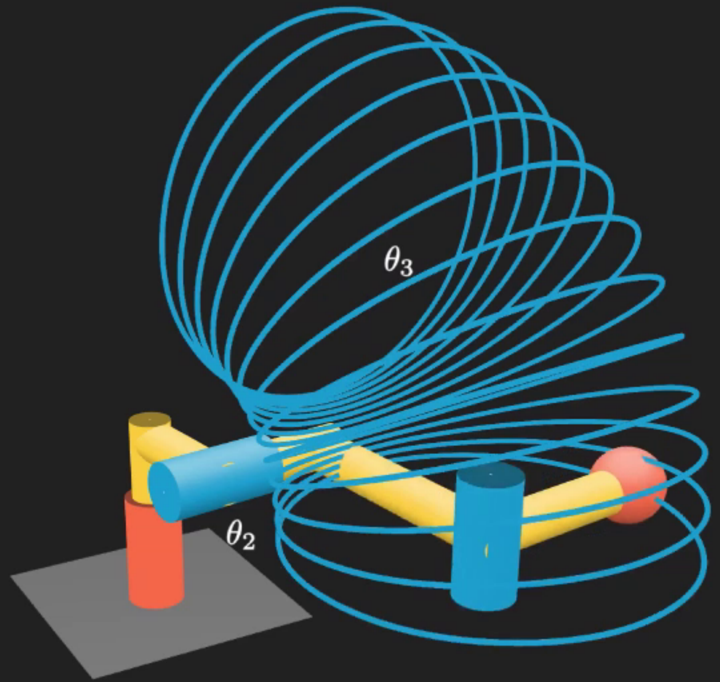

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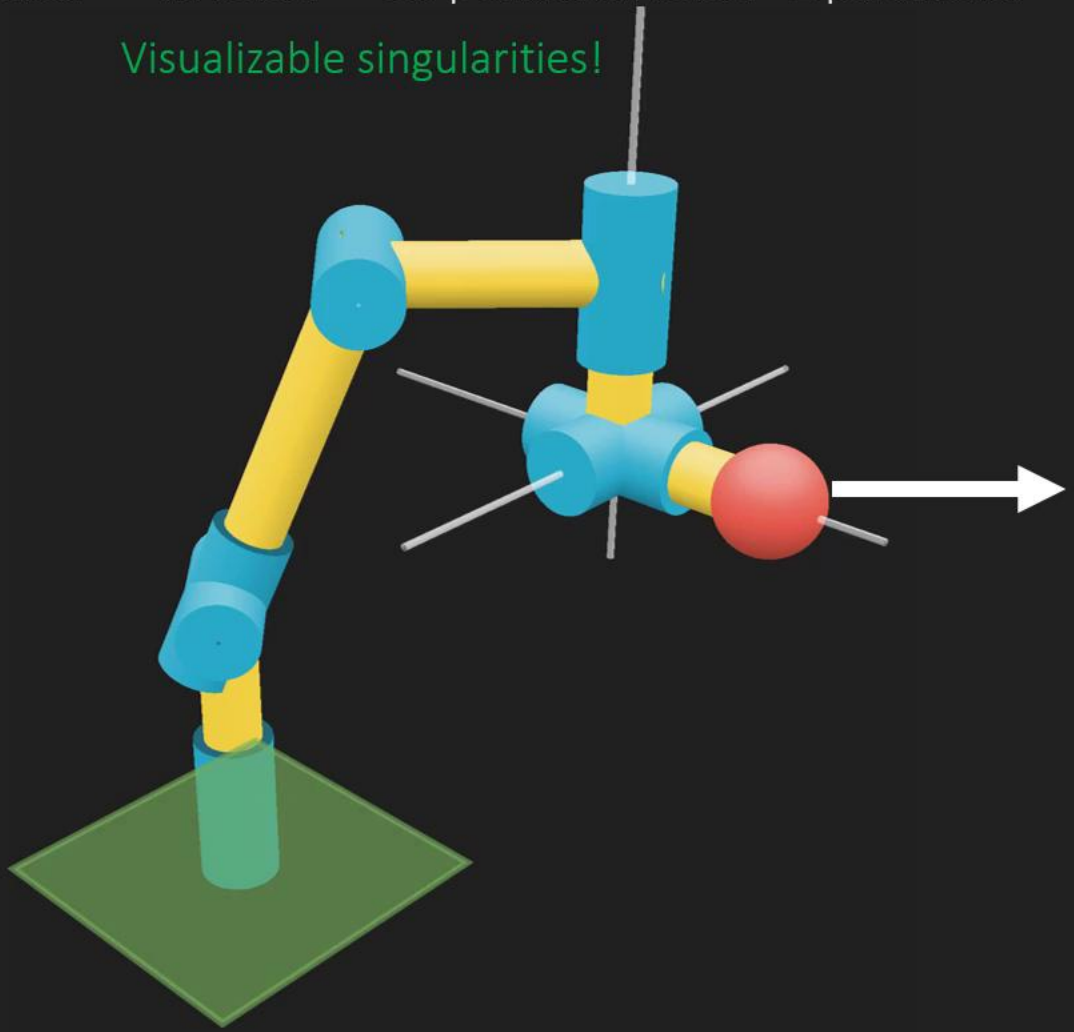

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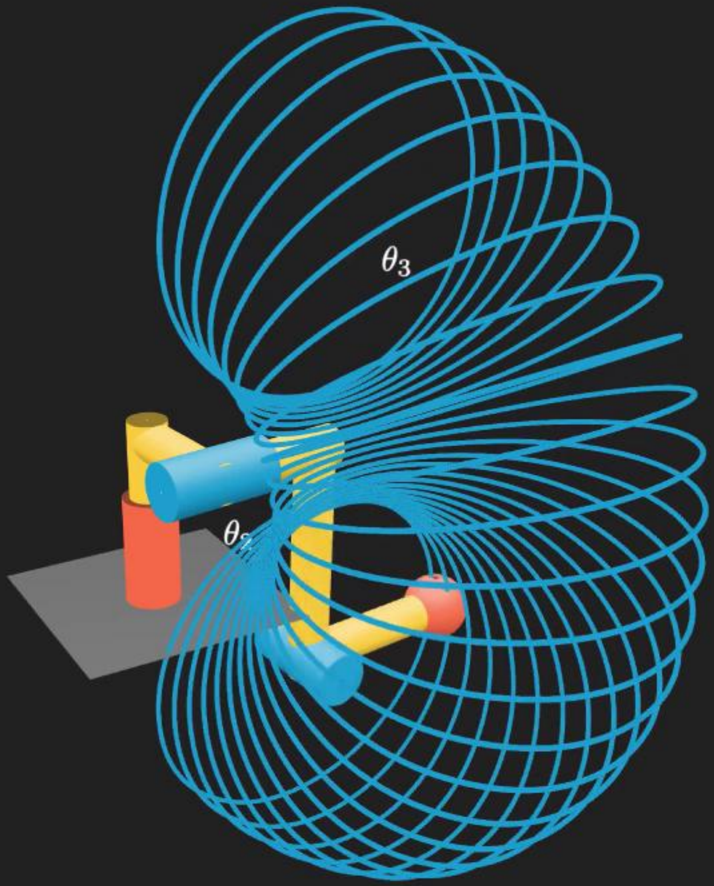

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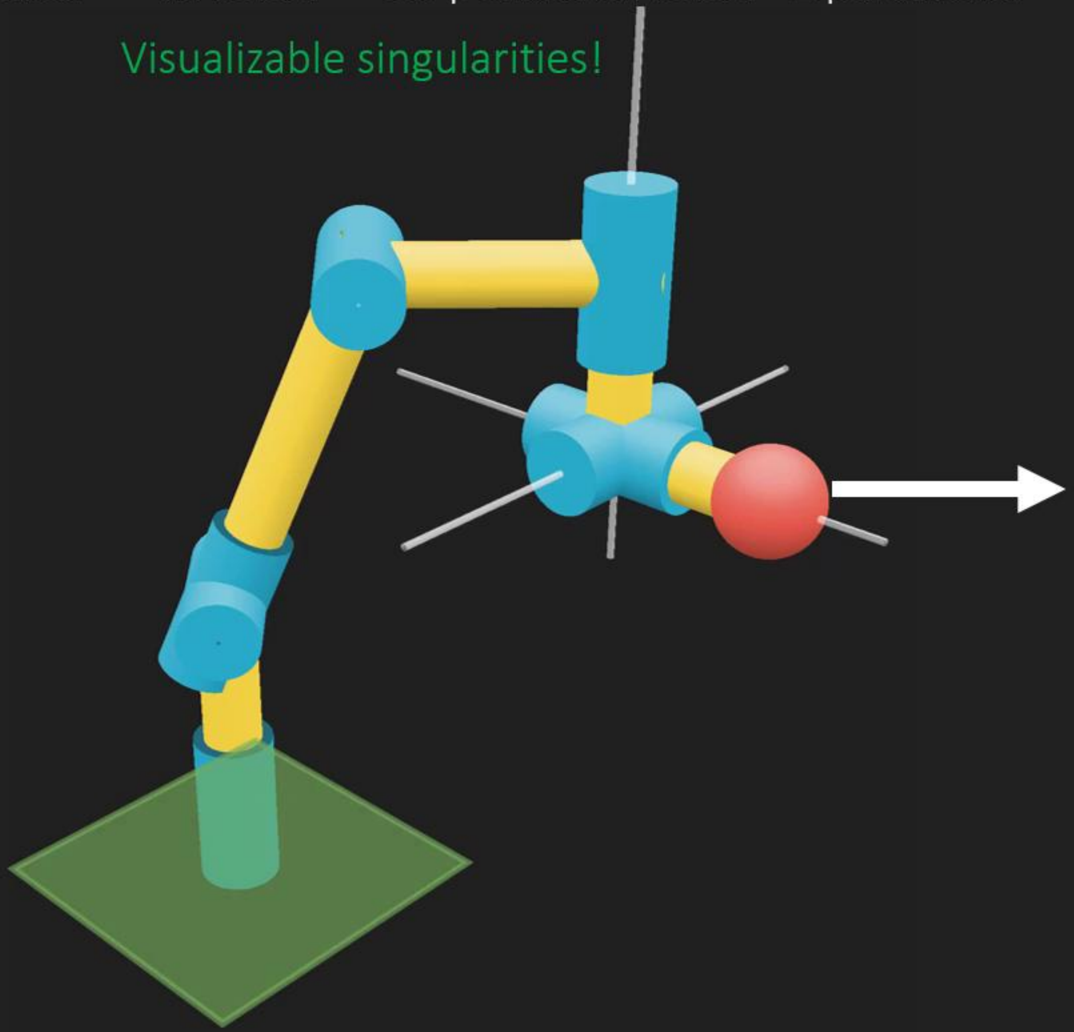

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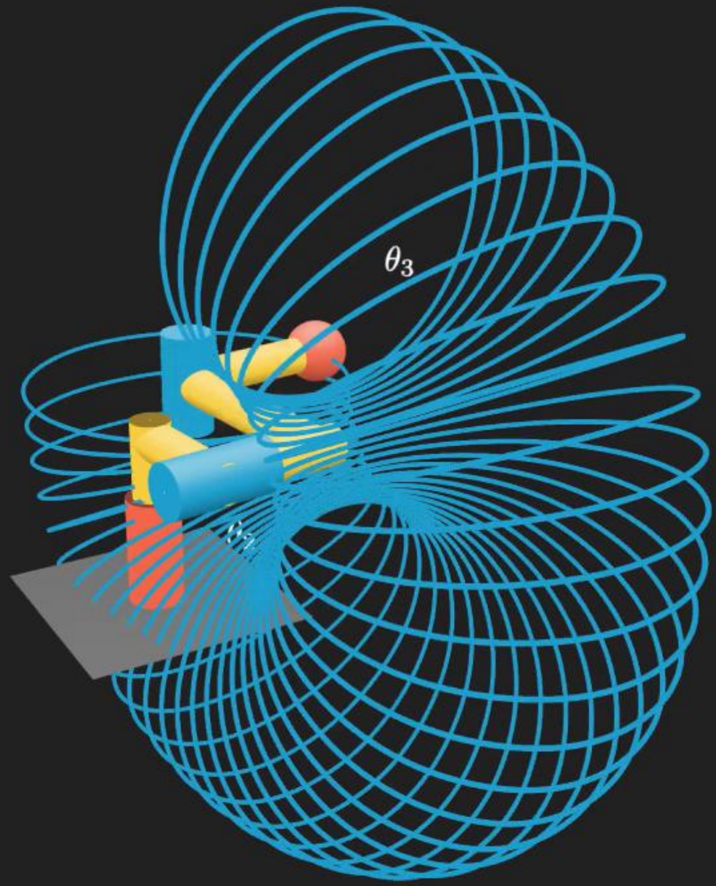

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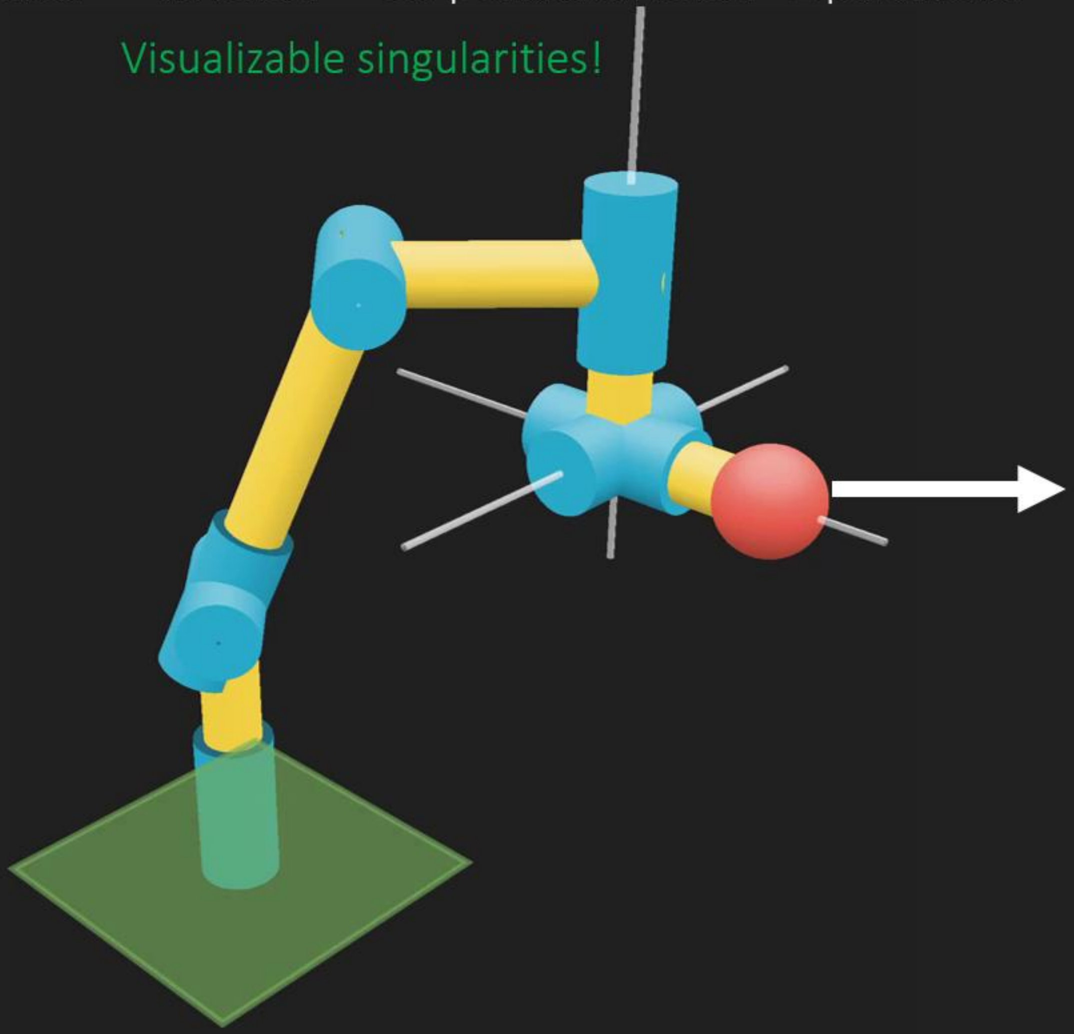

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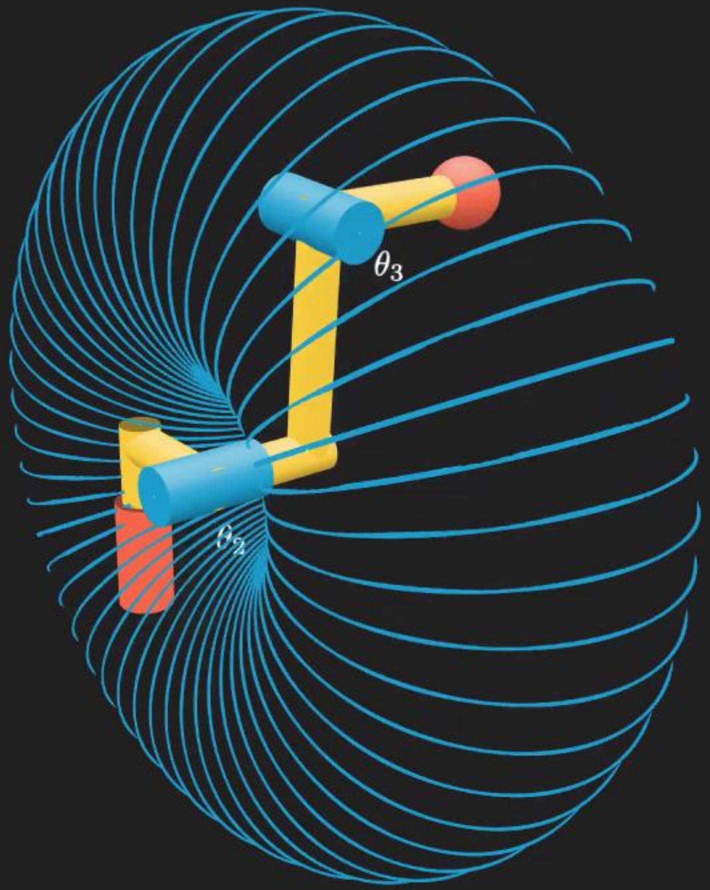

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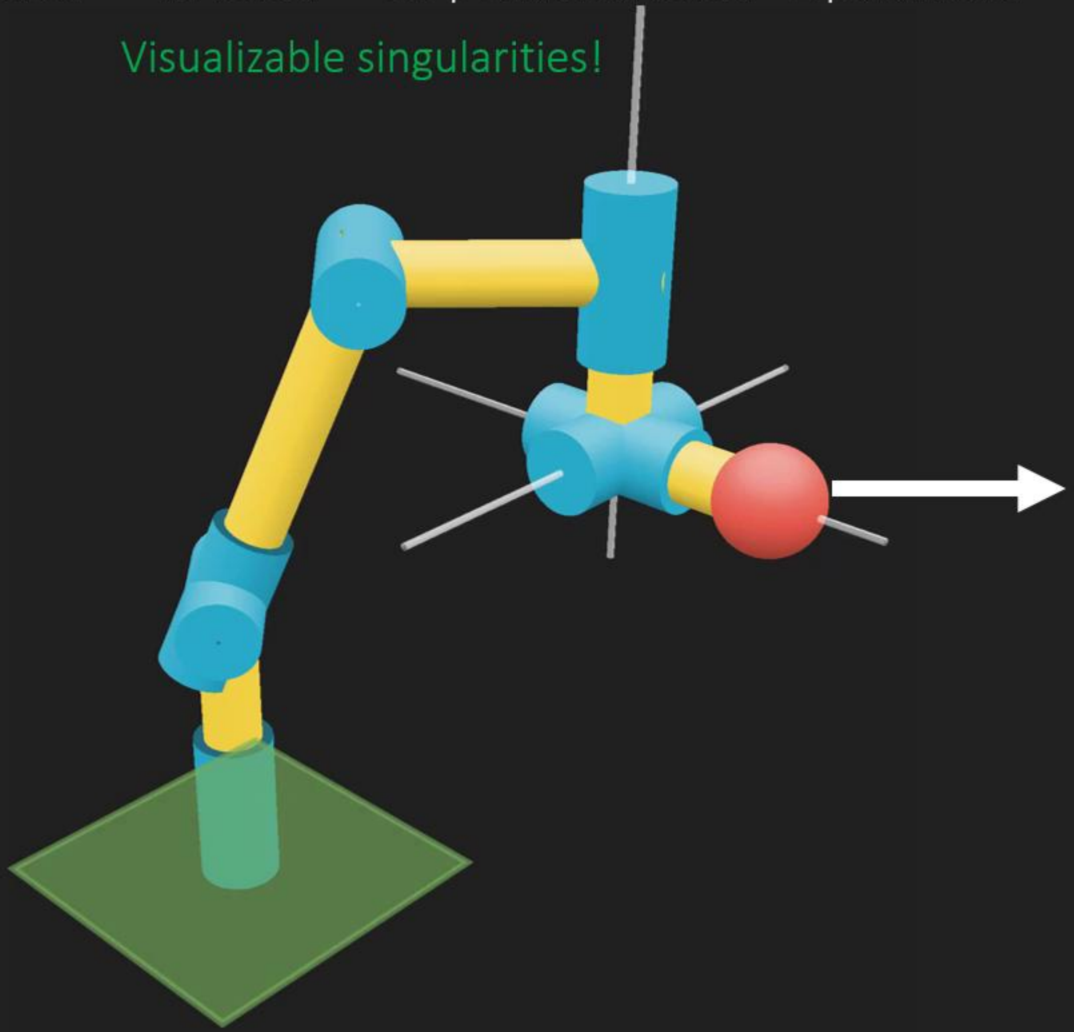

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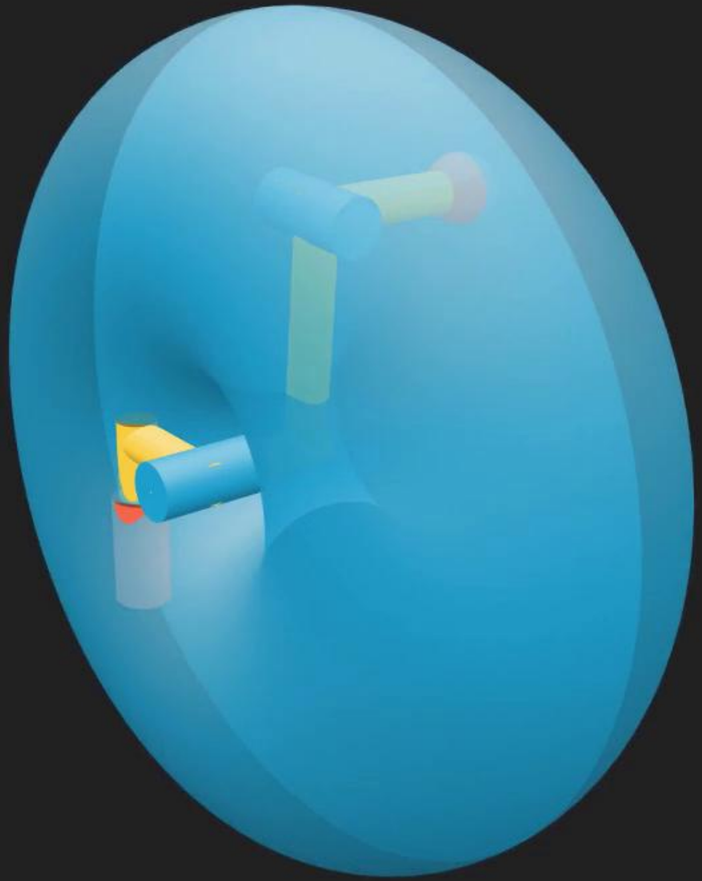
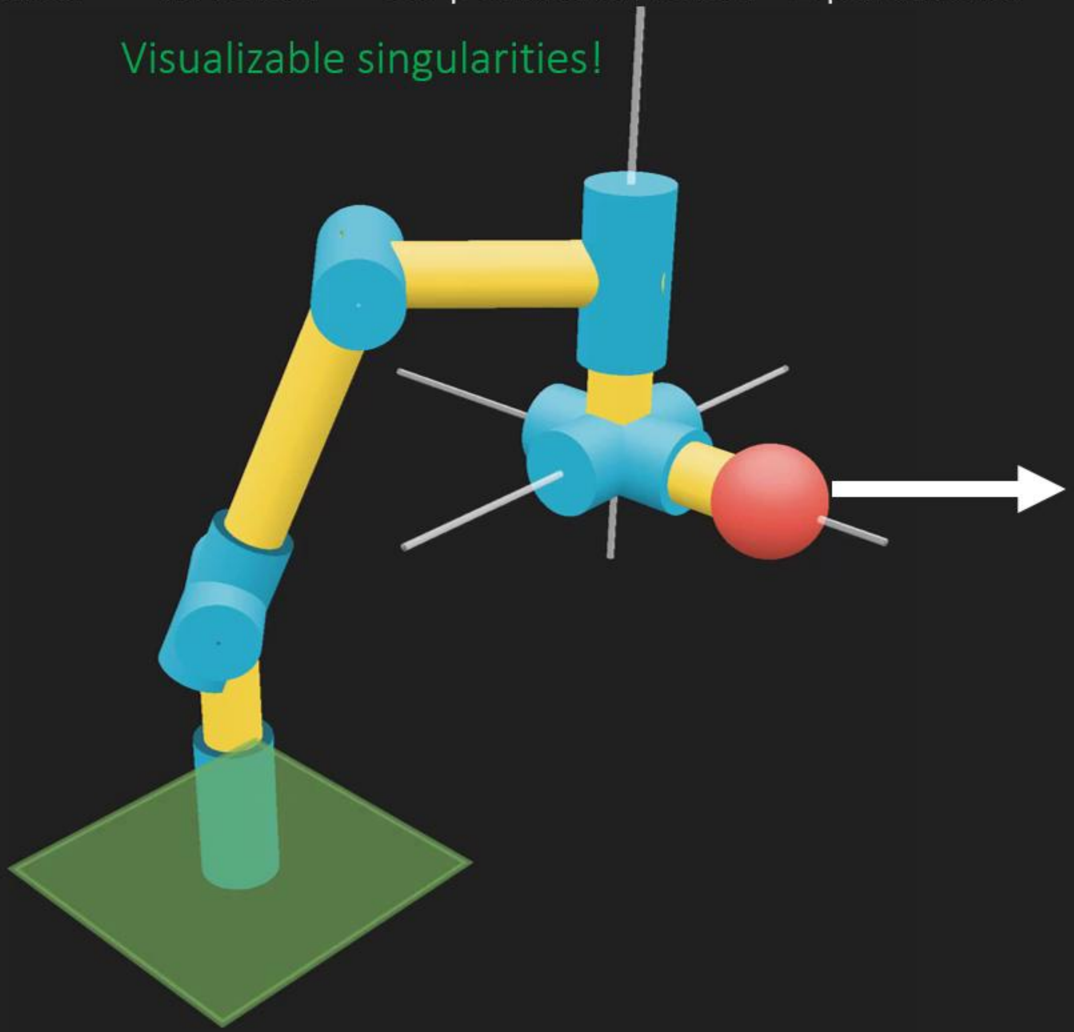


Axis 2: Kinematic analysis

7R robot => 4R robot => 3R positional robot+ 1 parameter

Visualizable singularities!



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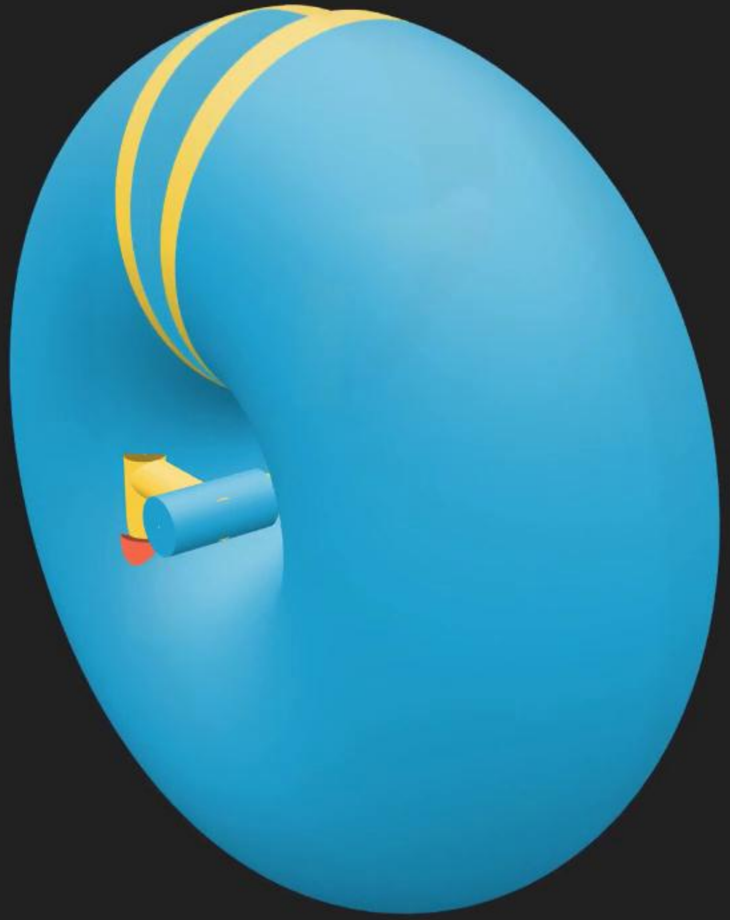

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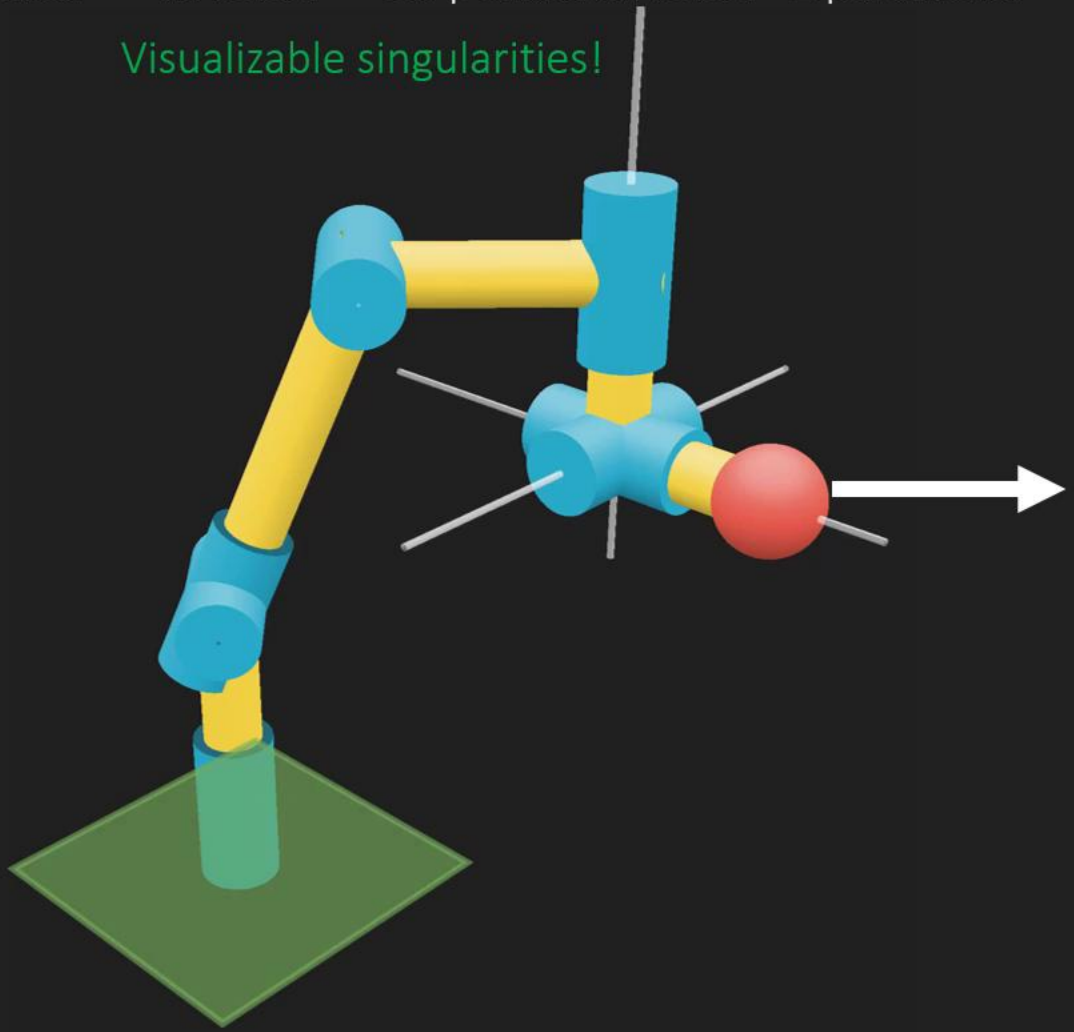

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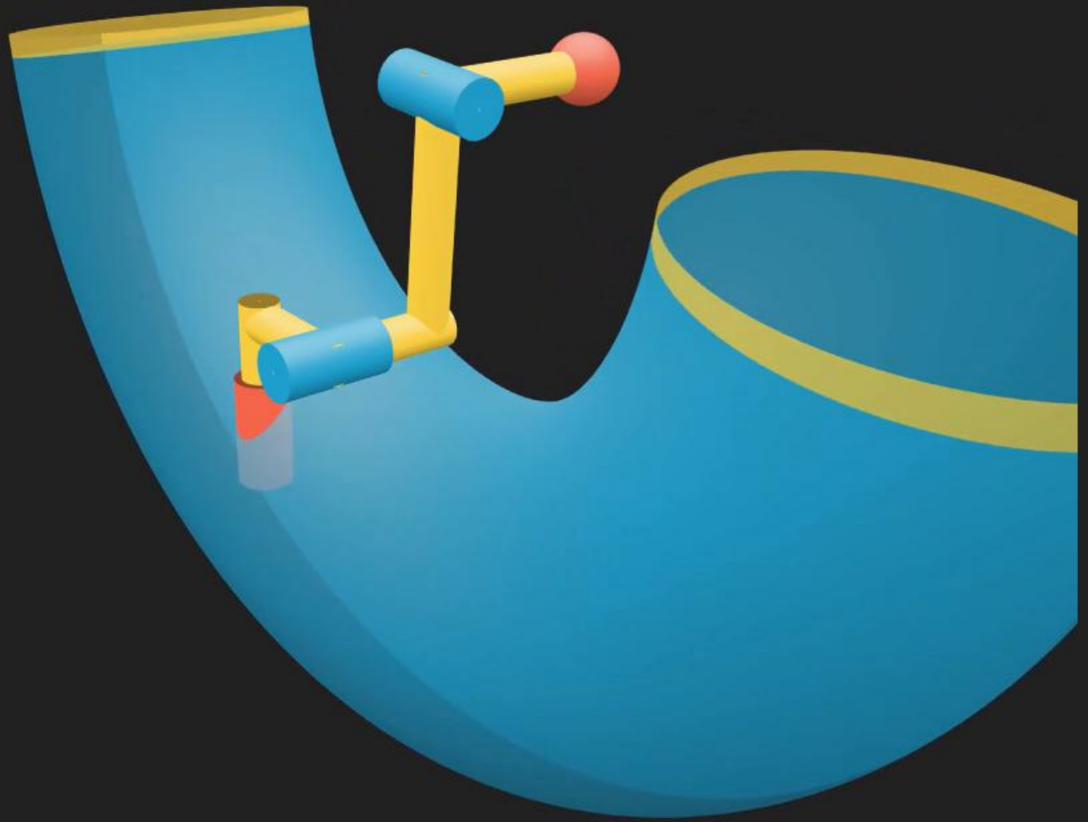

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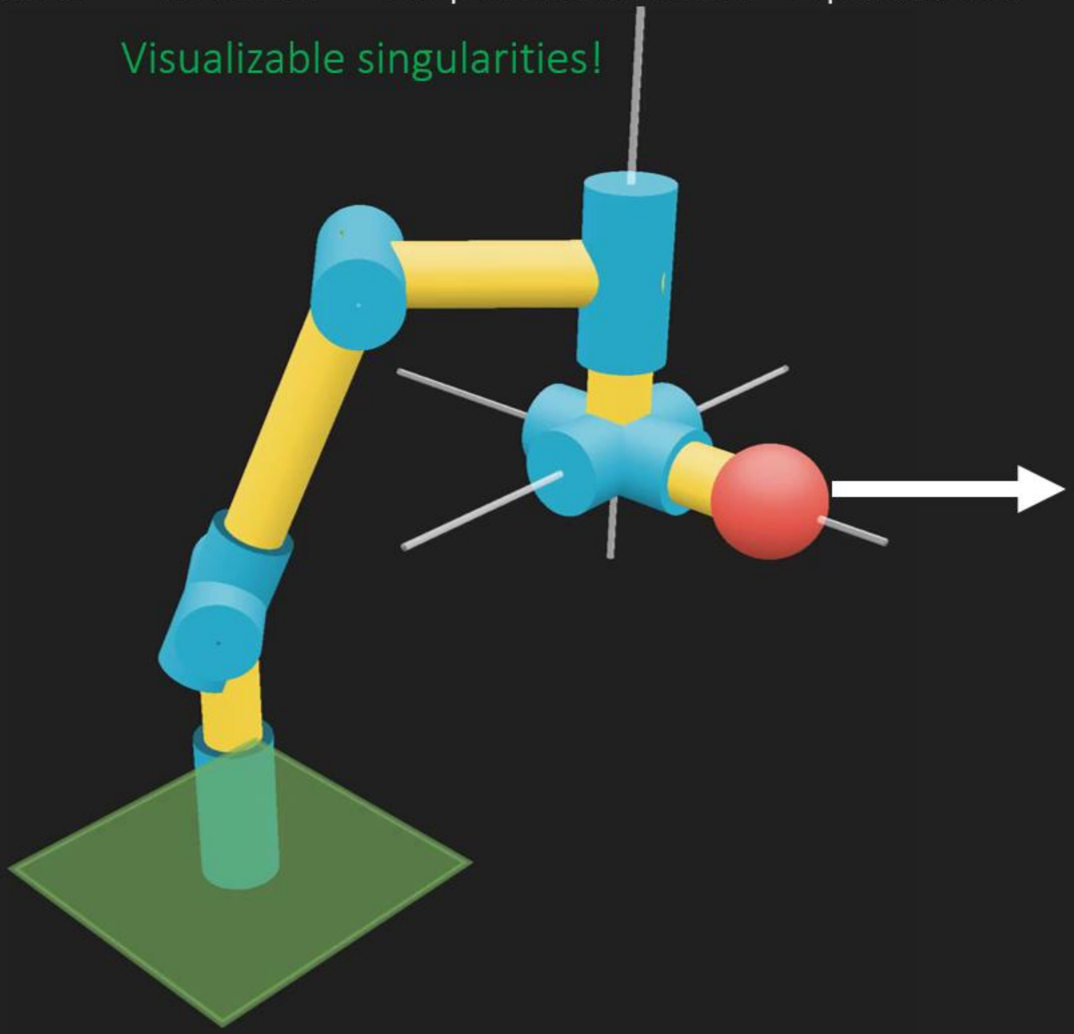

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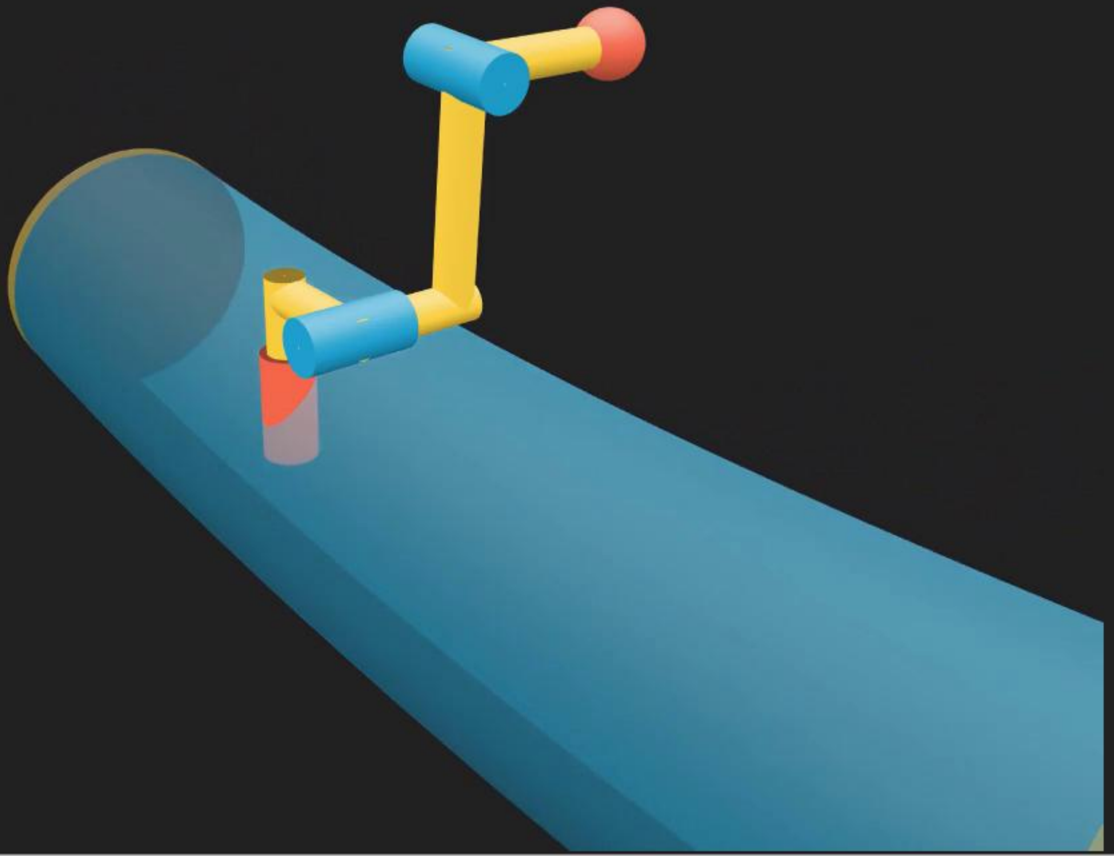

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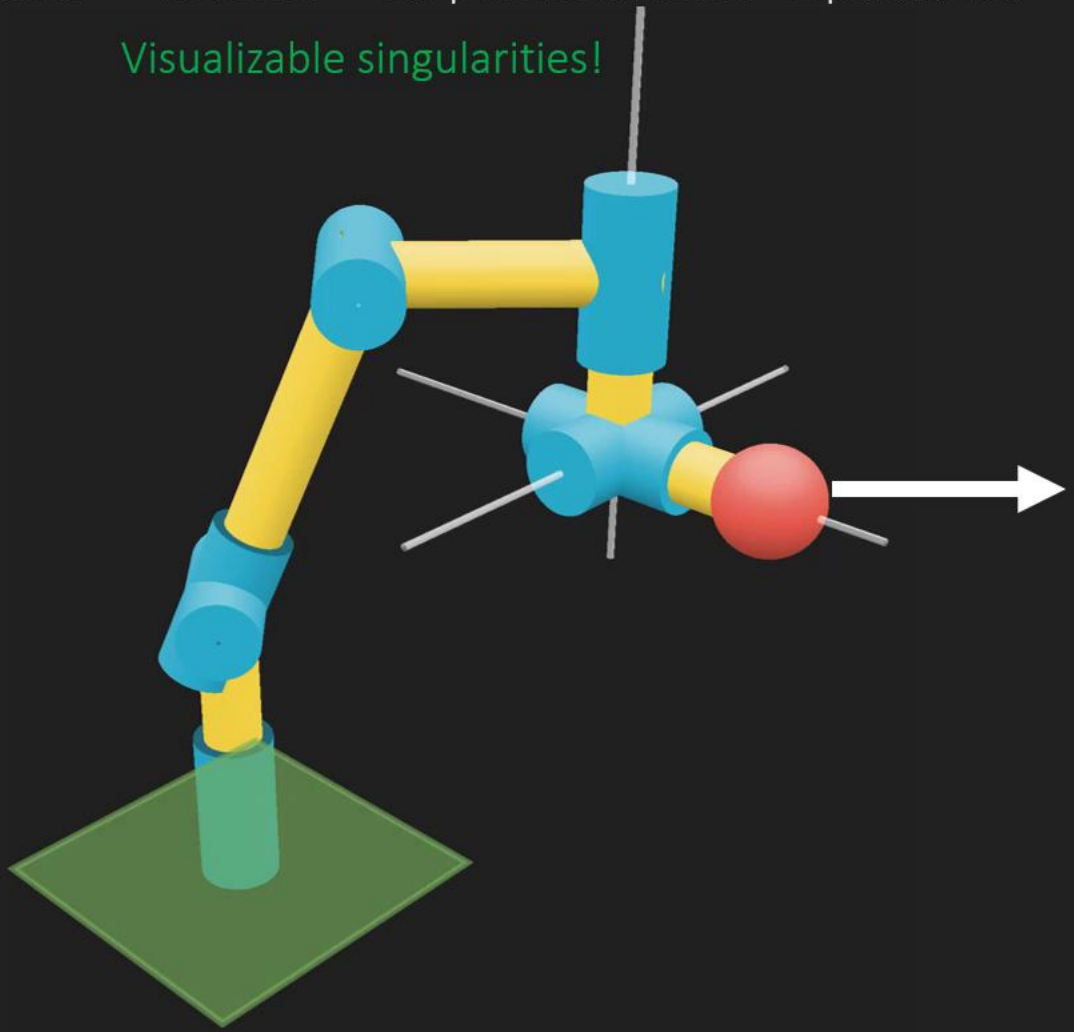

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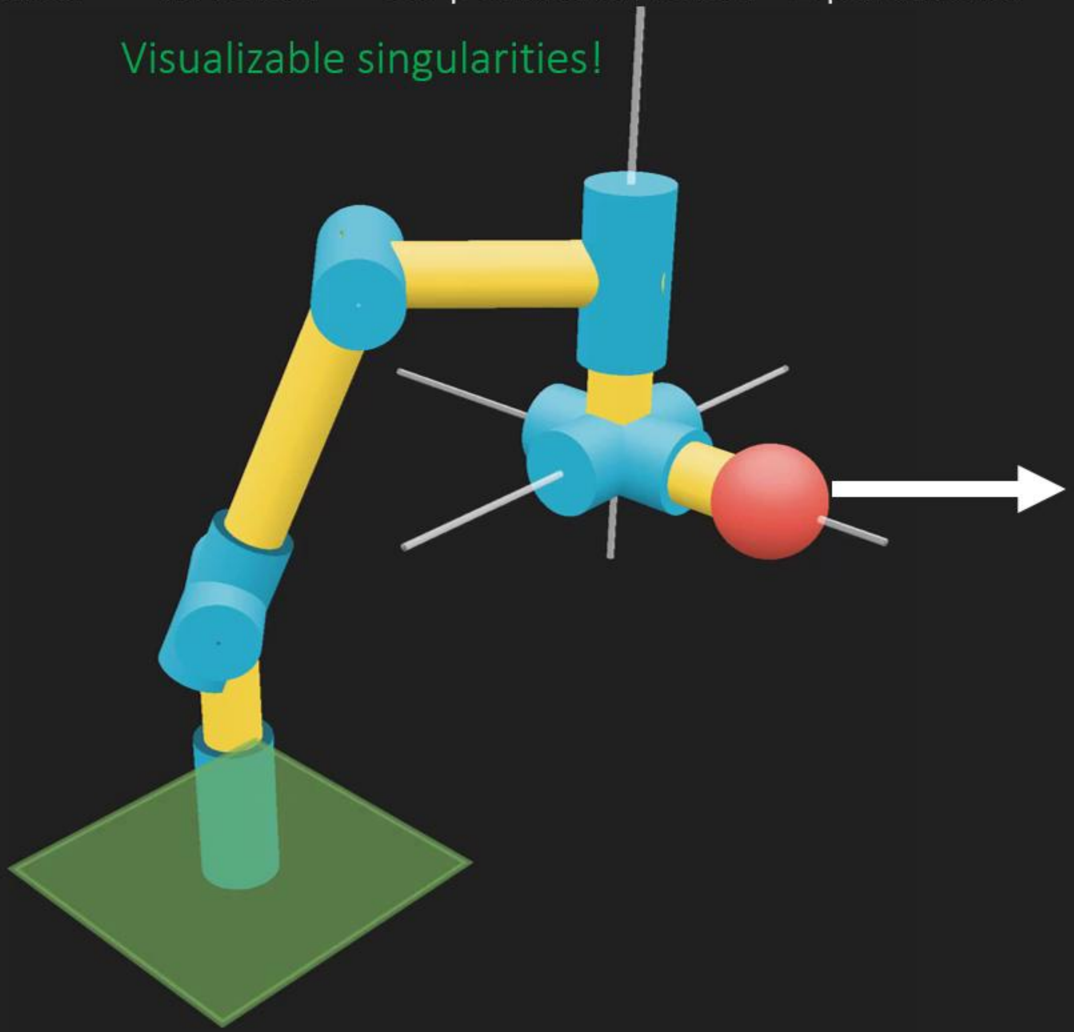

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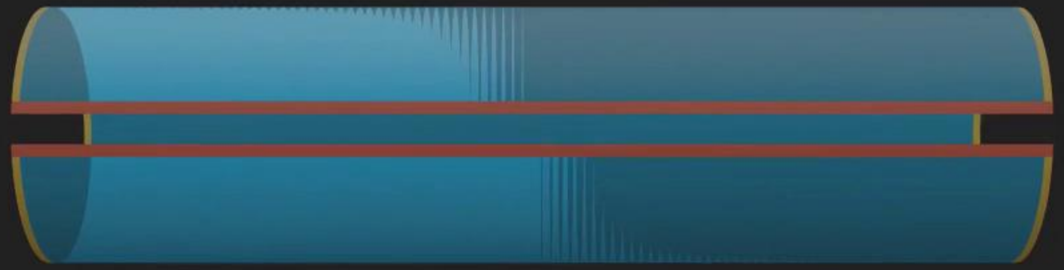

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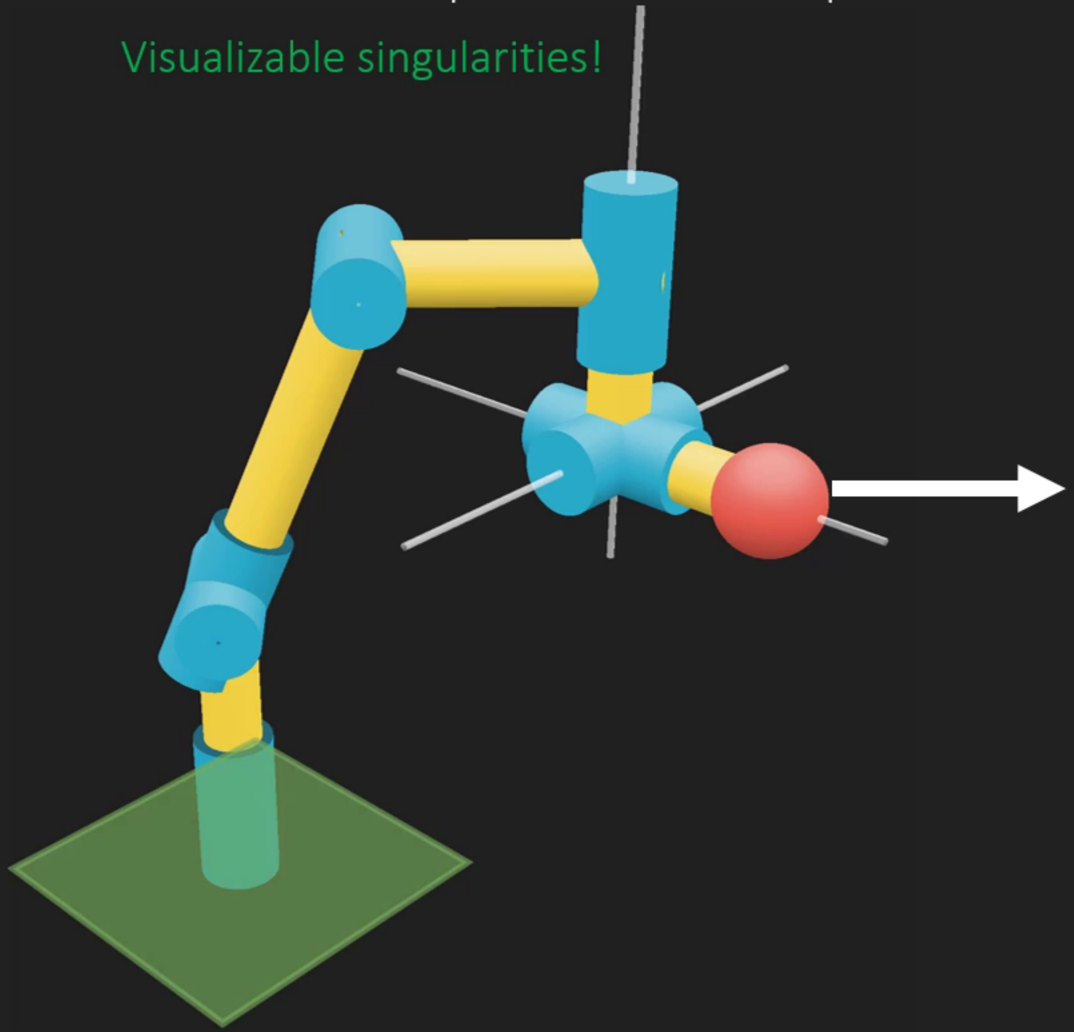

3R positional robot => reduced to only 2 parameters

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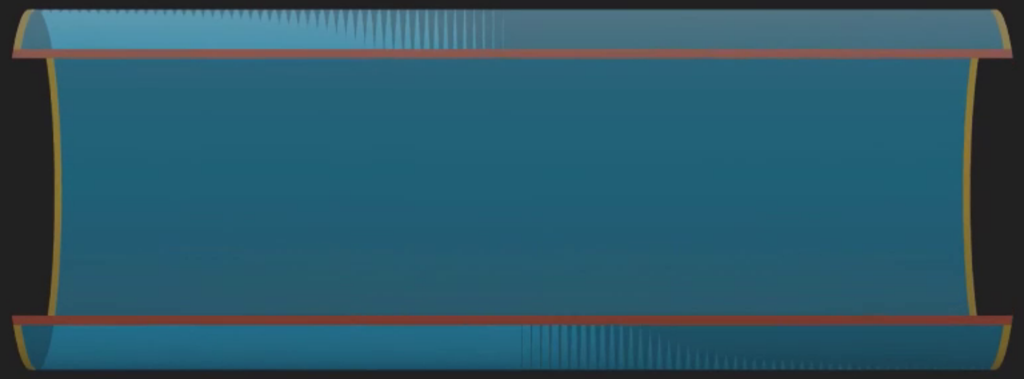

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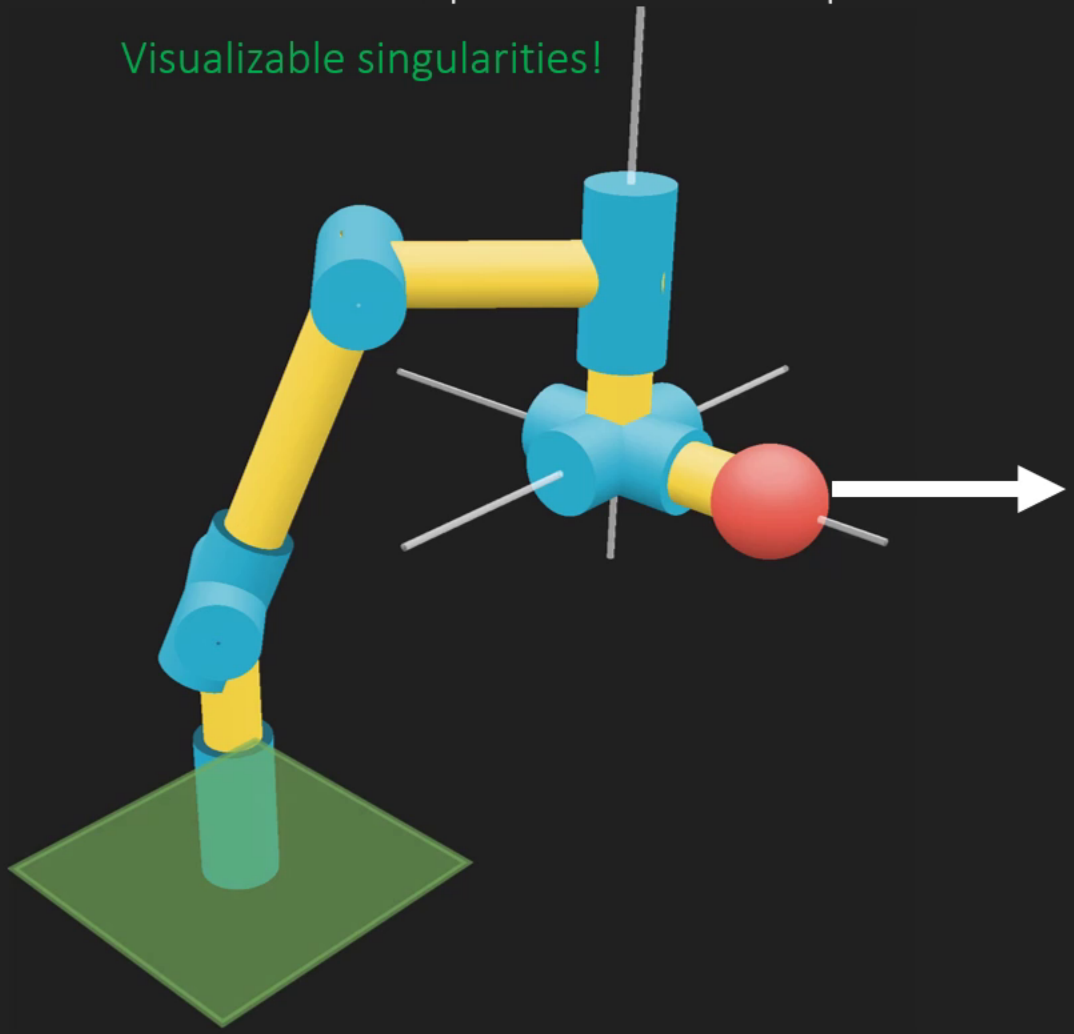

3R positional robot => reduced to only 2 parameters

Singularities plot in 2D plane

Axis 2: Kinematic analysis

7R => 4R => 3R + 1 => (2R + 1) + 1

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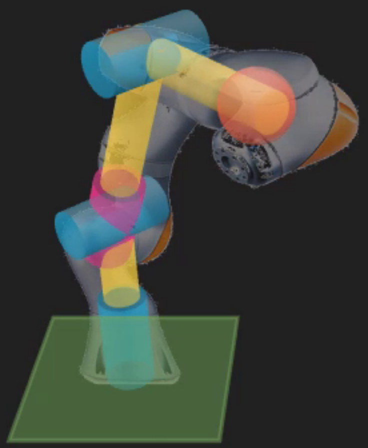
7R => 4R => 3R + 1 => (2R + 1) + 1



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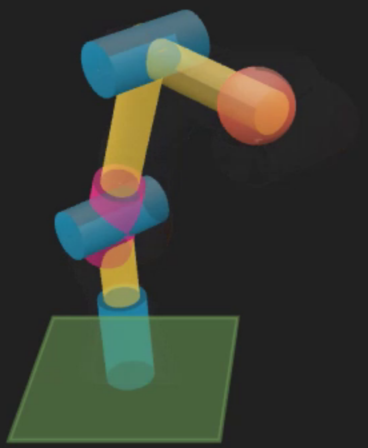

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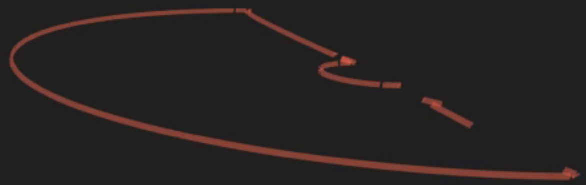
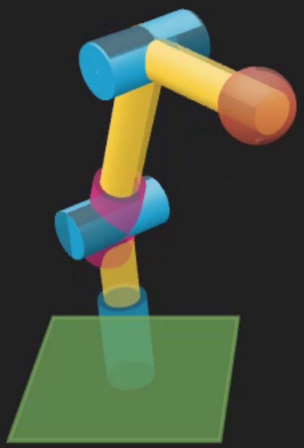




$\cos \alpha_2$

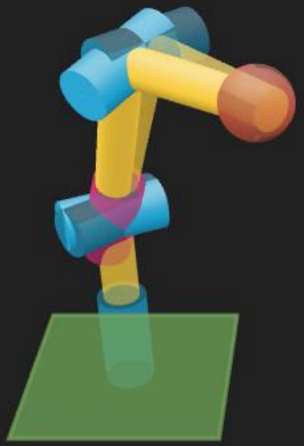
↓

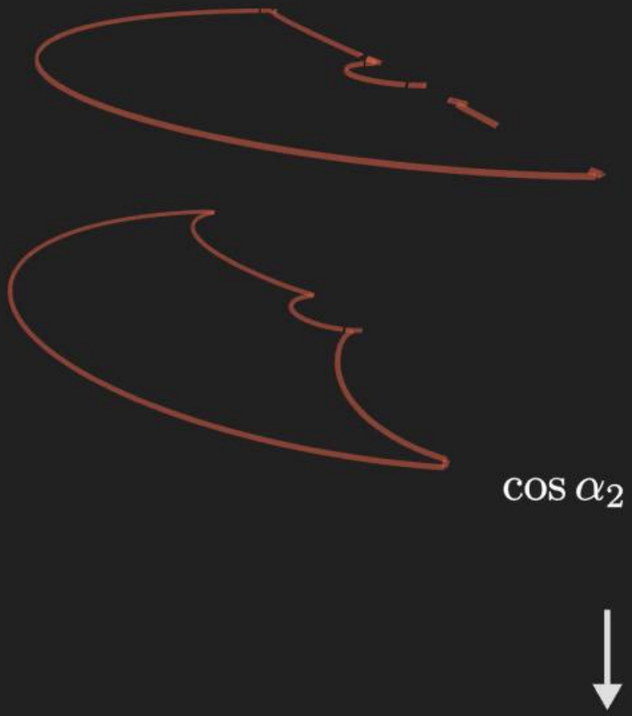
z

$$\rho = \sqrt{x^2 + y^2}$$

Axis 2: Kinematic analysis

7R => 4R => 3R + 1 => (2R + 1) + 1





Axis 2: Kinematic analysis

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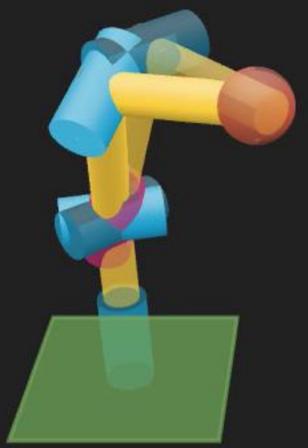
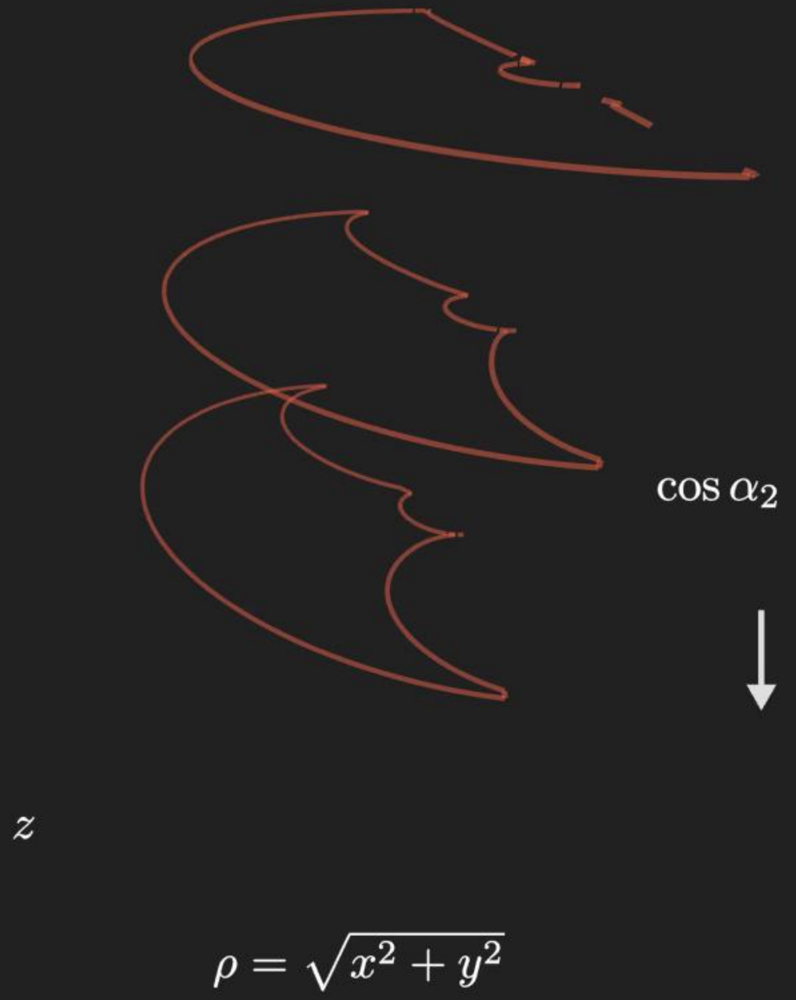

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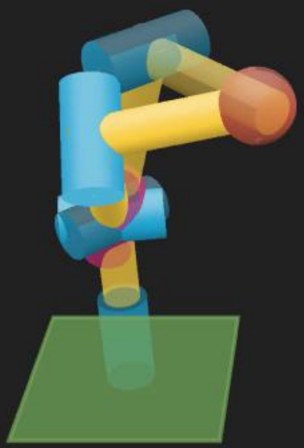
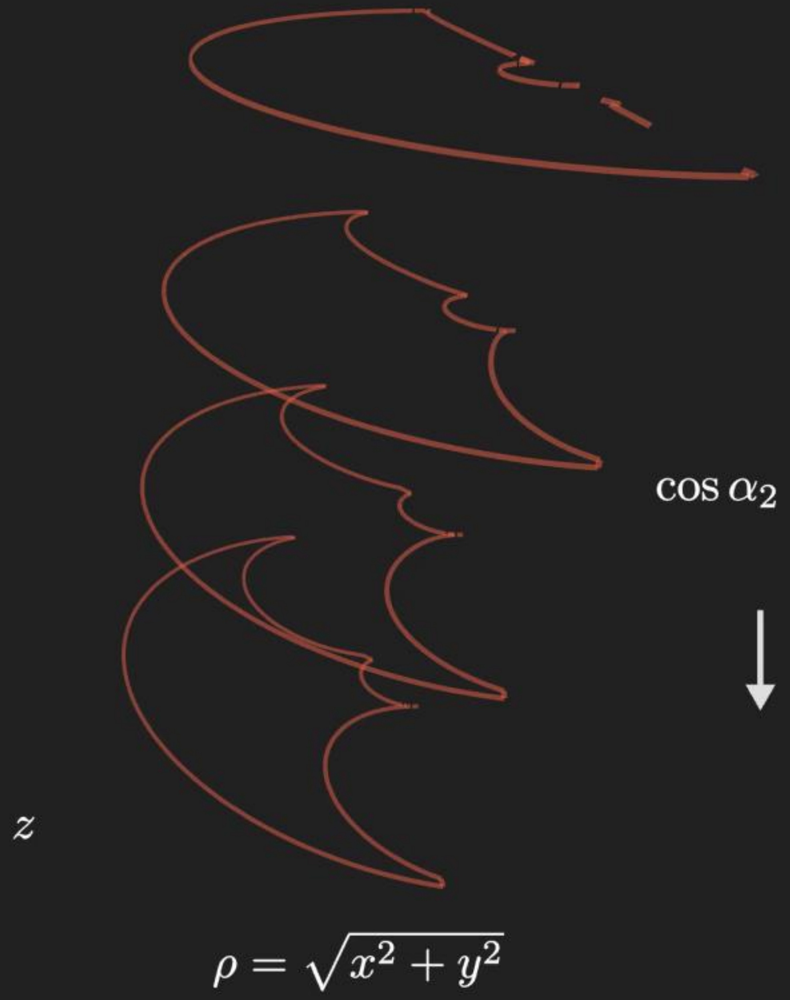
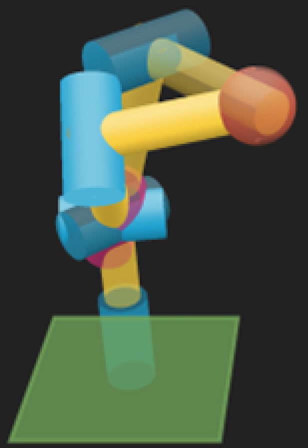


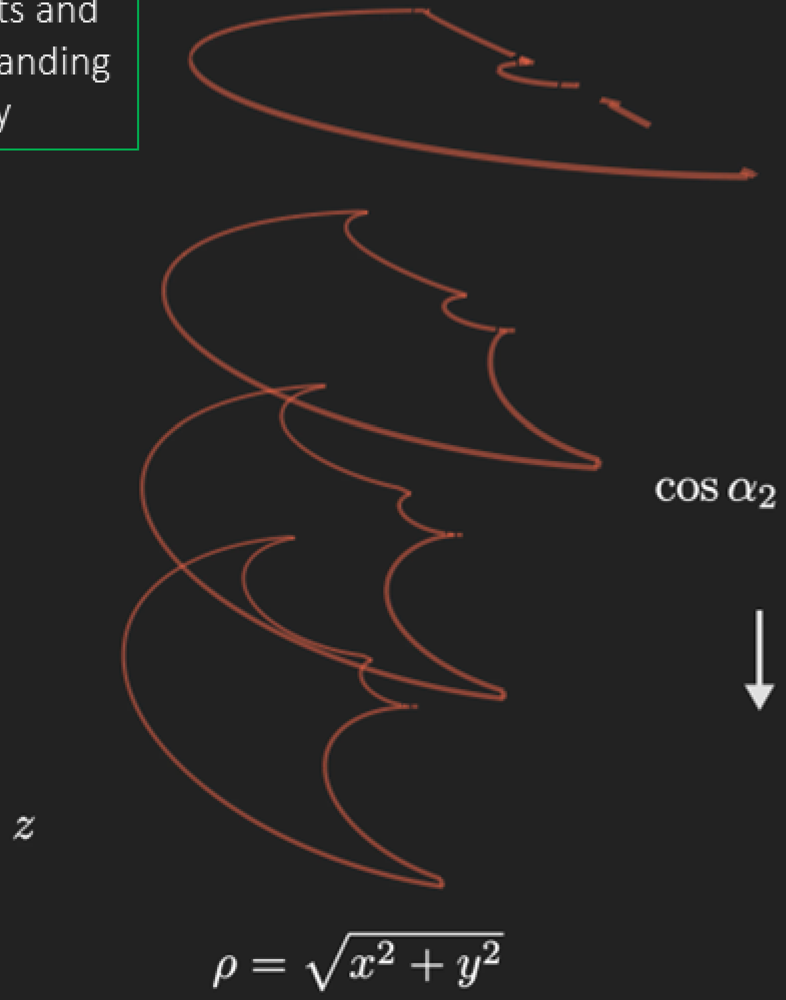


Axis 2: Kinematic analysis

7R => 4R => 3R + 1 => (2R + 1) + 1

Impossible to visualize singularity → Geometric insights and complete understanding of singularity





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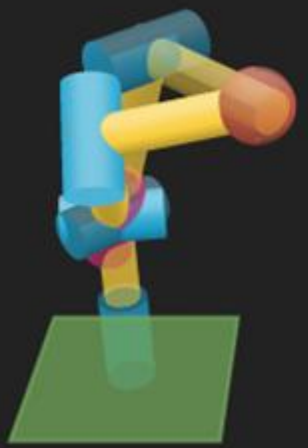

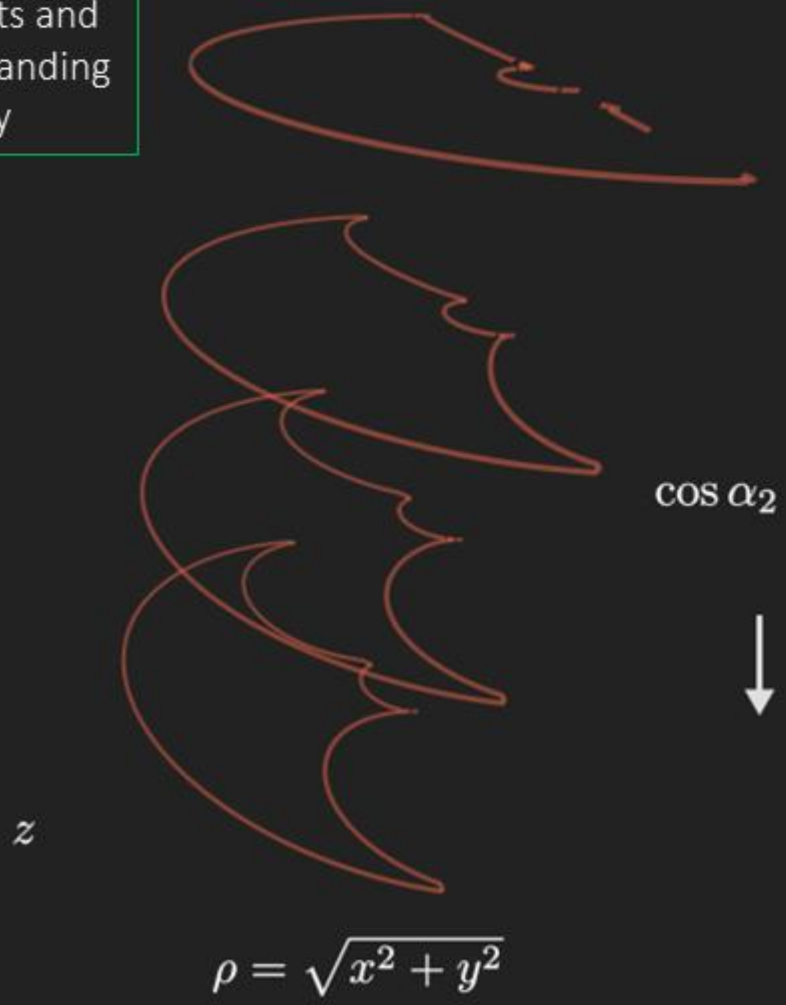

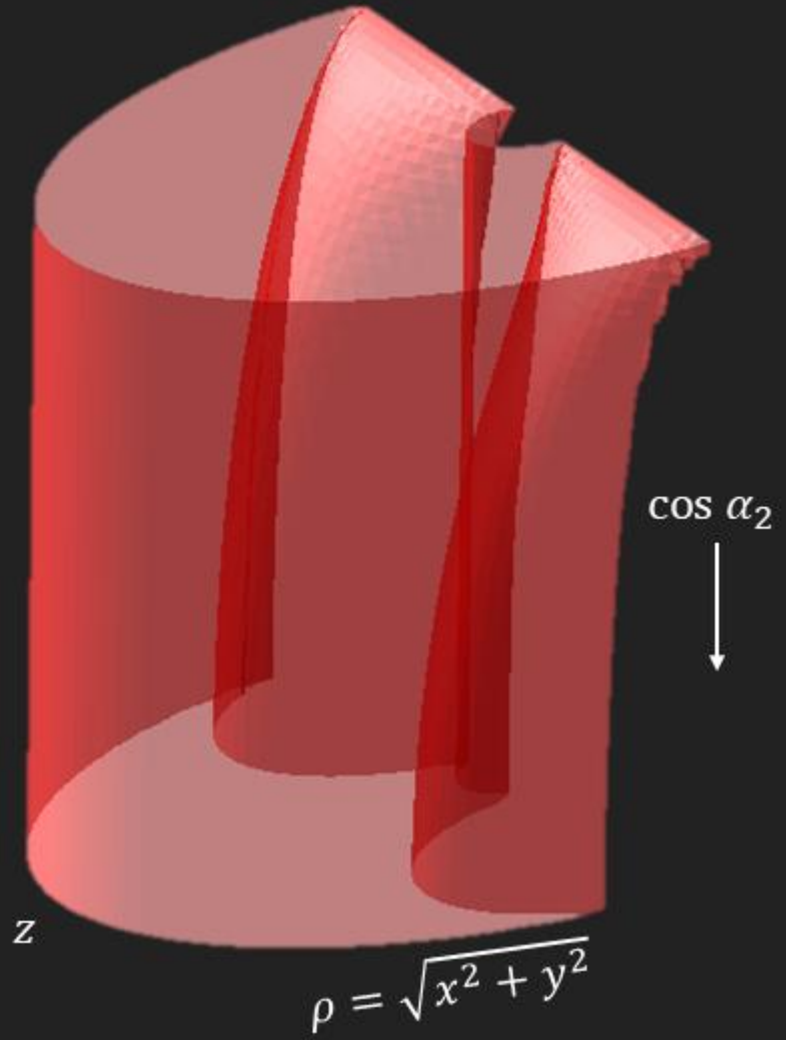

Choice of host laboratories

Team RDH

Le laboratoire des sciences de l'ingénieur, de l'informatique et de l'imagerie (UMR7357) (ICube)

Strasbourg

Choice of host laboratories

Team RDH

Le laboratoire des sciences de l'ingénieur, de l'informatique et de l'imagerie (UMR7357) (ICube)

Strasbourg

Team Gepetto

Laboratoire de recherche spécialisé dans l’analyse et l’architecture des systèmes (UPR 8001) (LAAS)

Toulouse

Integration: Team RDH, ICube, Strasbourg

Parallel robots

Medical robotics

Path planning

Kinematic analysis

Cuspidal robots

Optimisation

Geometric Algebra

Learning from demonstration

Transfer learning

Integration: Team RDH, ICube, Strasbourg

Parallel robots

Medical robotics

Path planning

Complements team's existing expertise

Pierre Renaud

Florent Nageotte

Kinematic analysis

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Kinematic analysis | Cuspidal robots | Optimisation

I bring my research expertise

Geometric Algebra | Learning from demonstration | Transfer learning

I contribute in expanding the current expertise of the team

Olivier Piccin

Nicolas Padoy

Integration: Team RDH, ICube, Strasbourg

Infrastructure

A

Infrastructure

1. Collaborative robots, redundant robots (x 2) (Fig. A)

A

Integration: Team RDH, ICube, Strasbourg

Infrastructure

1. Collaborative robots, redundant robots (x 2) (Fig. A)

2. Haptic teleoperating system (Fig: B)

A

B

Integration: Team RDH, ICube, Strasbourg

Infrastructure

1. Collaborative robots, redundant robots (x 2) (Fig. A)

2. Haptic teleoperating system (Fig: B)

3. Strong collaboration with medical teams (IHU + Camma) (Fig. B, C)

A

B

C

Integration: Team RDH, ICube, Strasbourg

Infrastructure

1. Collaborative robots, redundant robots (x 2) (Fig. A)

2. Haptic teleoperating system (Fig: B)

3. Strong collaboration with medical teams (IHU + Camma) (Fig. B, C)

A

B

C

Perfect environment to extend learning from demonstration in medical applications !

Integration: Team Gepetto, LAAS, Toulouse

Path planning

Optimisation

Transfer learning

Kinematic analysis

Cuspidal robots

Parallel robots

Geometric Algebra

Learning from demonstration

Integration: Team Gepetto, LAAS, Toulouse

LAAS CNRS

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Philippe Souères | Simon Lacroix (RIS) | Olivier Stasse

Kinematic analysis | Cuspidal robots | Parallel robots

I bring my research expertise

Geometric Algebra | Learning from demonstration

I contribute in expanding the current expertise of the team

References

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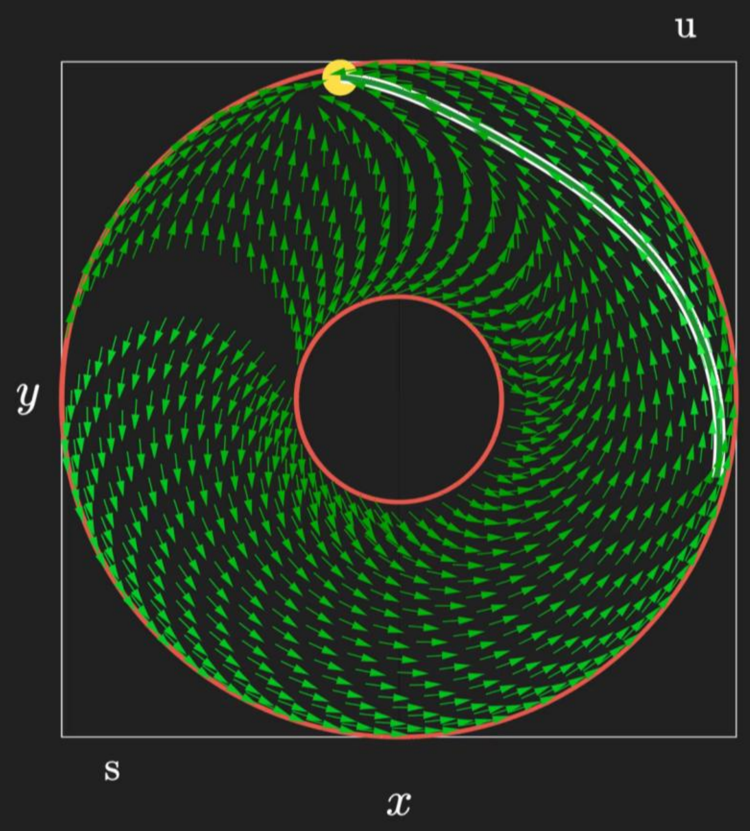
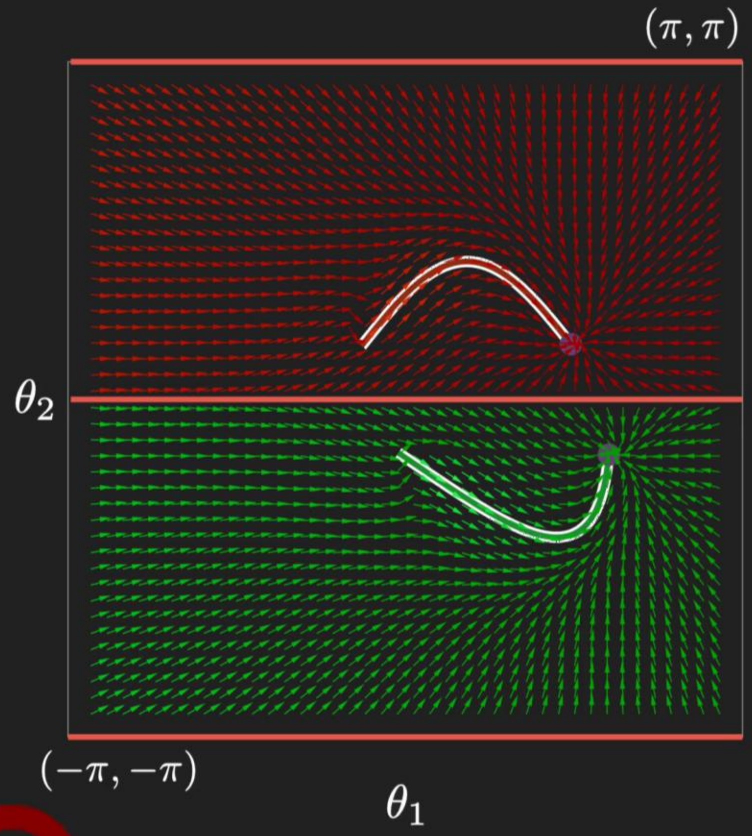
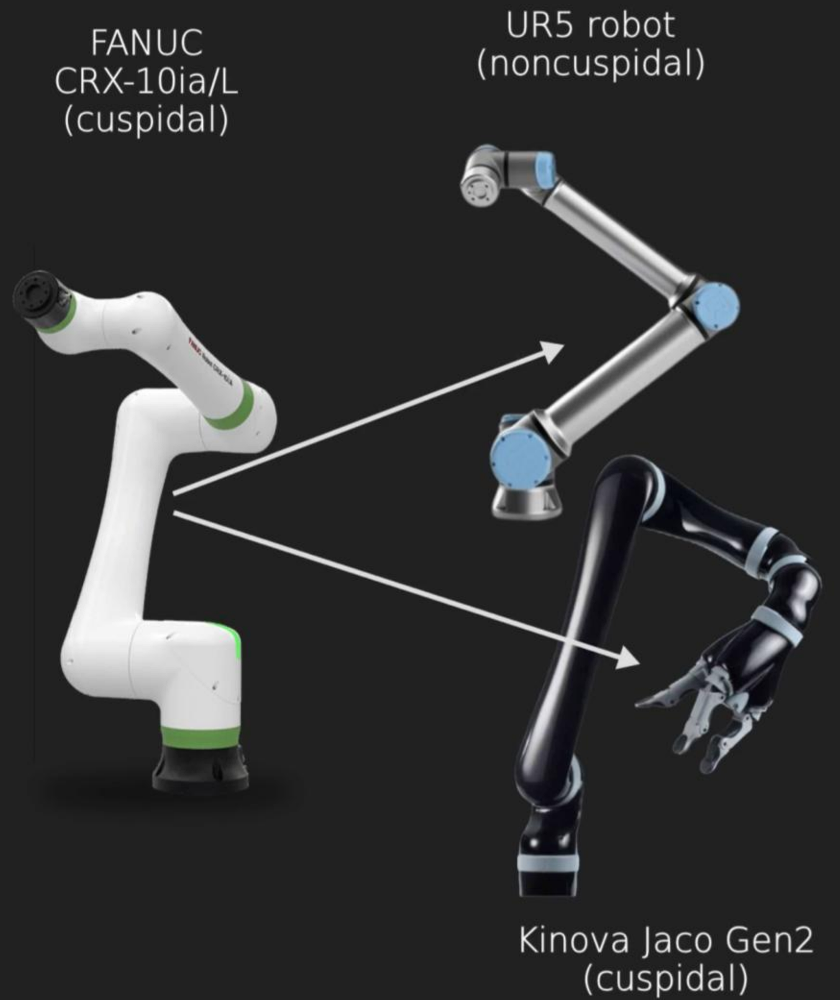
Annexes

Axis 3: Transfer of behaviour



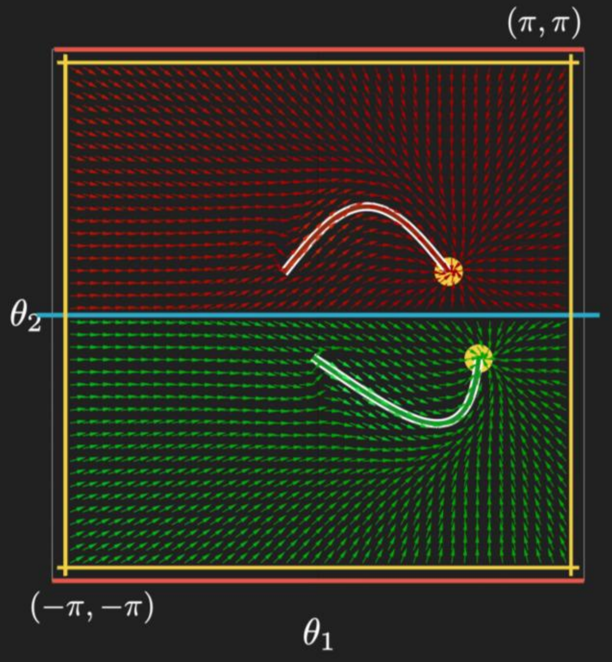




How can I TRANSFER behaviour among robots?

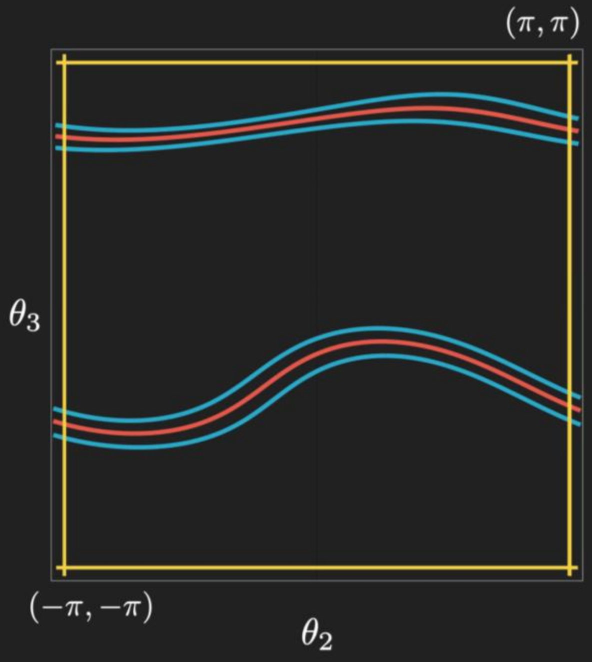
Axis 3: Transfer of behaviour

Generalized behaviour in robot 1



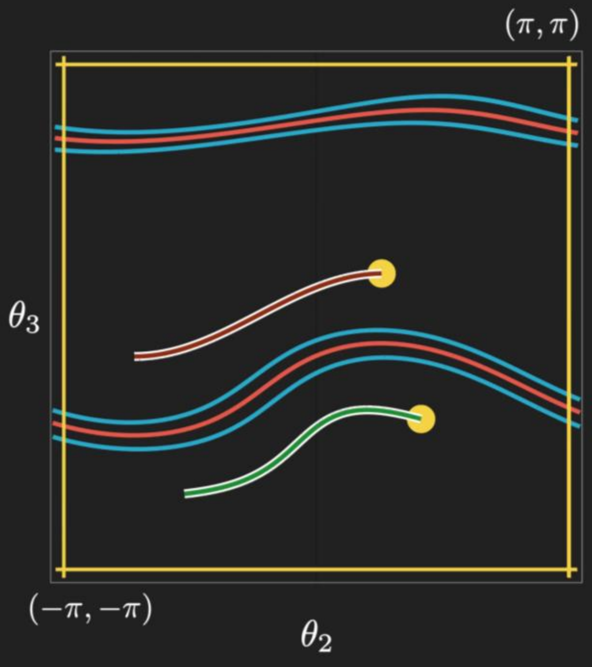
Singularities in joint space of 2R robot

Singularities of robot 2



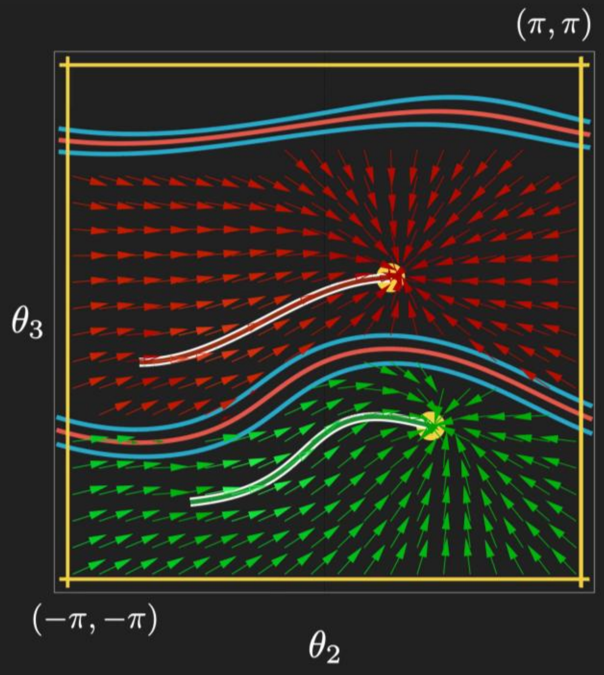
Singularities in joint space of 3R robot

Transfer of demonstration



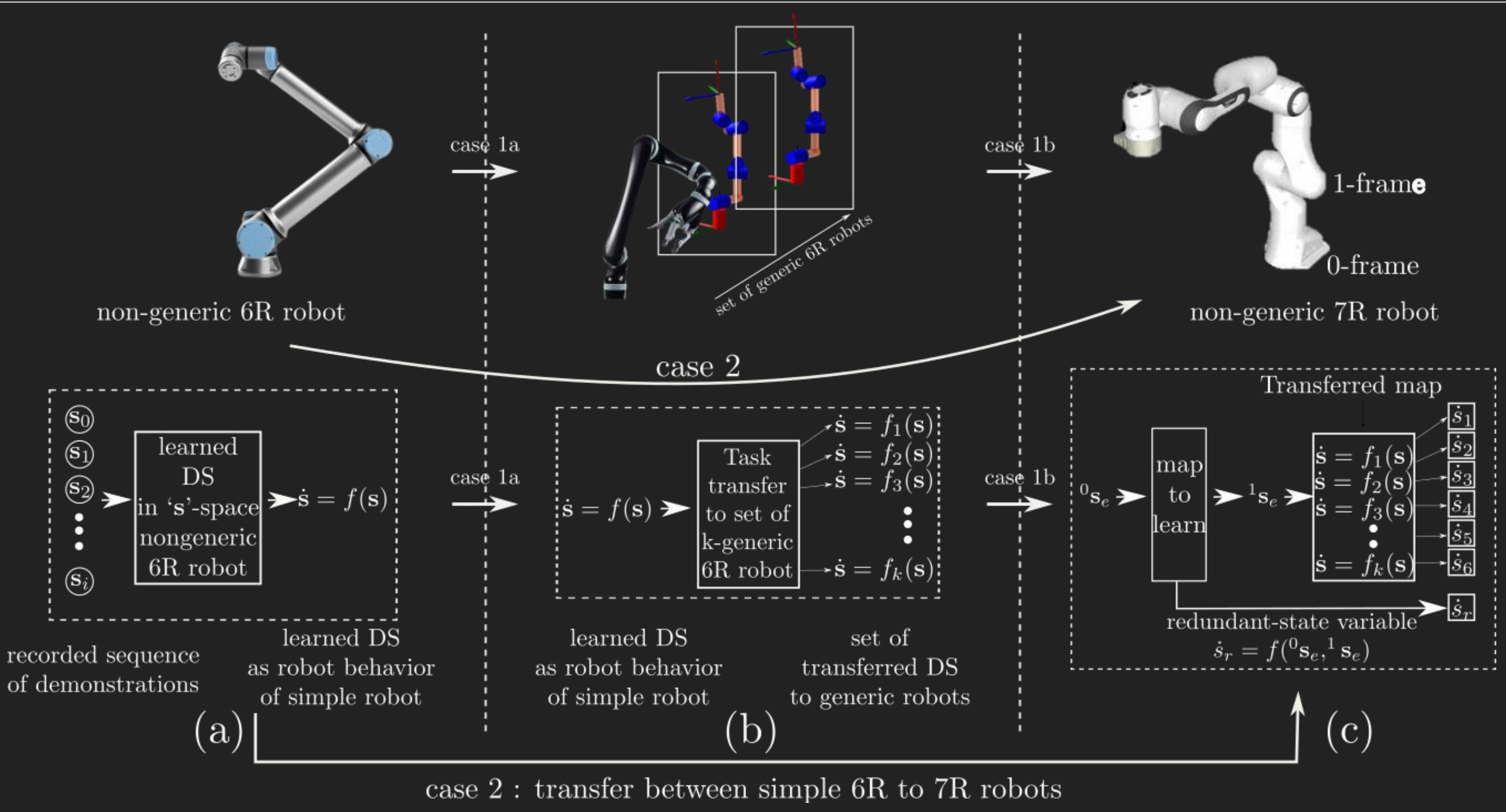
Singularities in joint space of 3R robot

Transfer of behavior



Singularities in joint space of 3R robot

Axis 3: Transfer of behaviour



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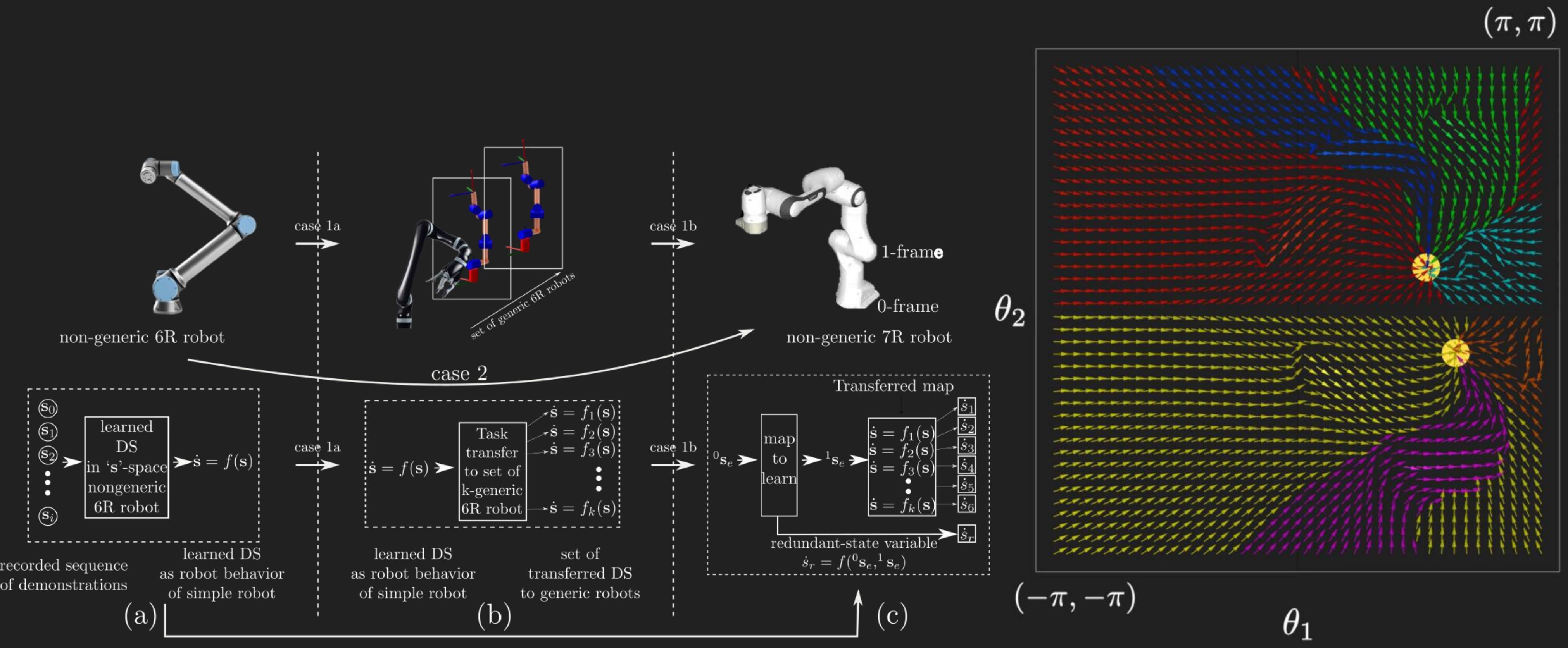

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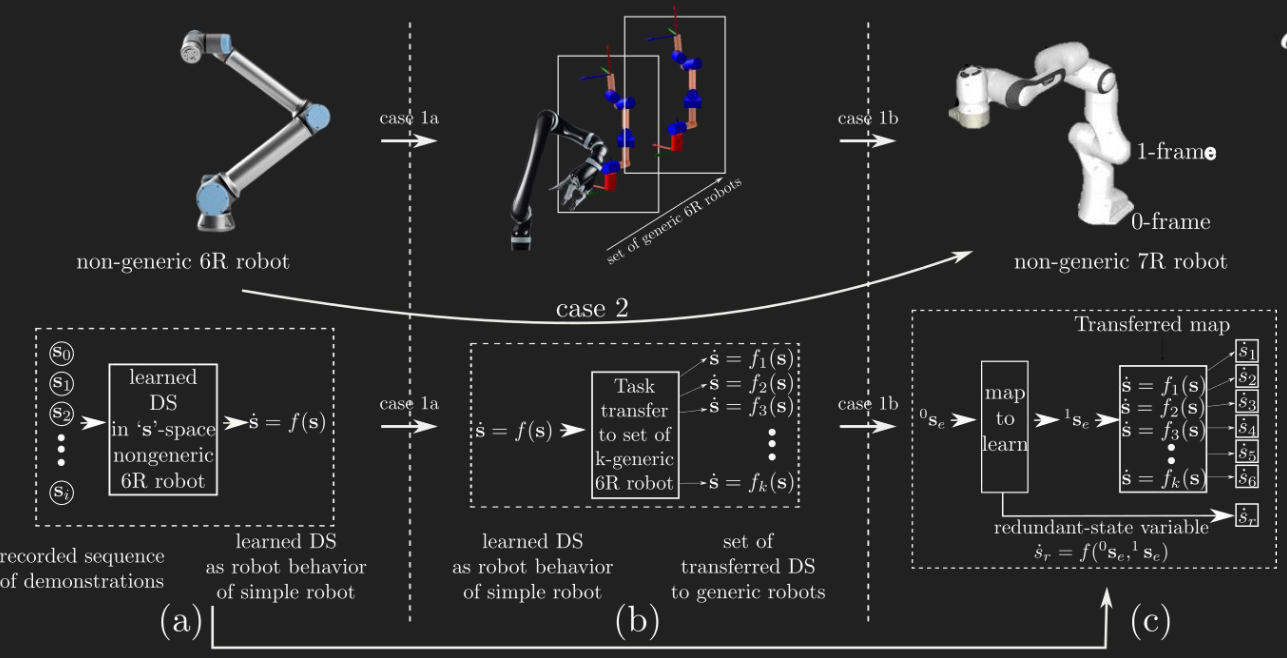
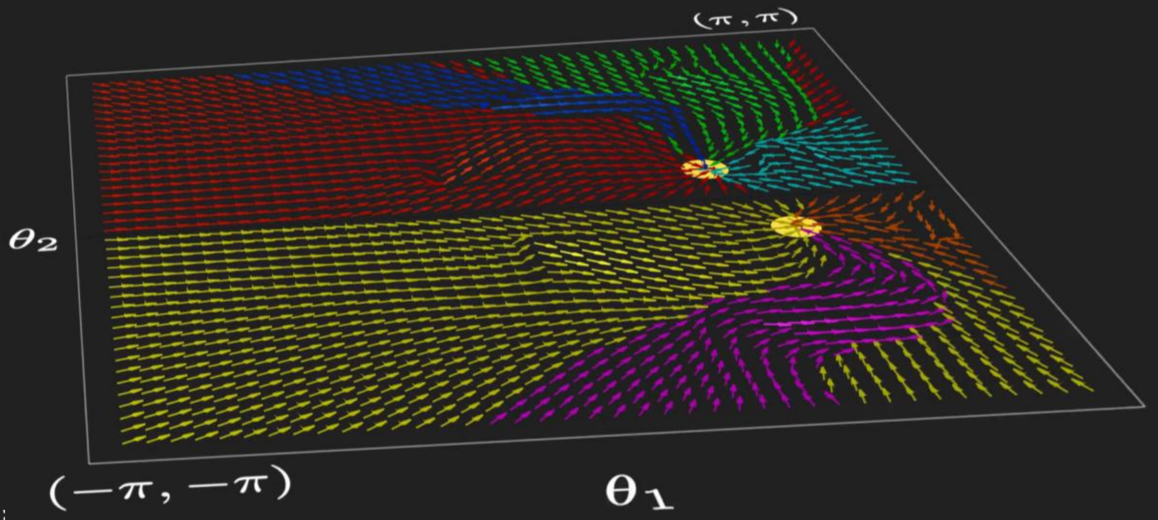
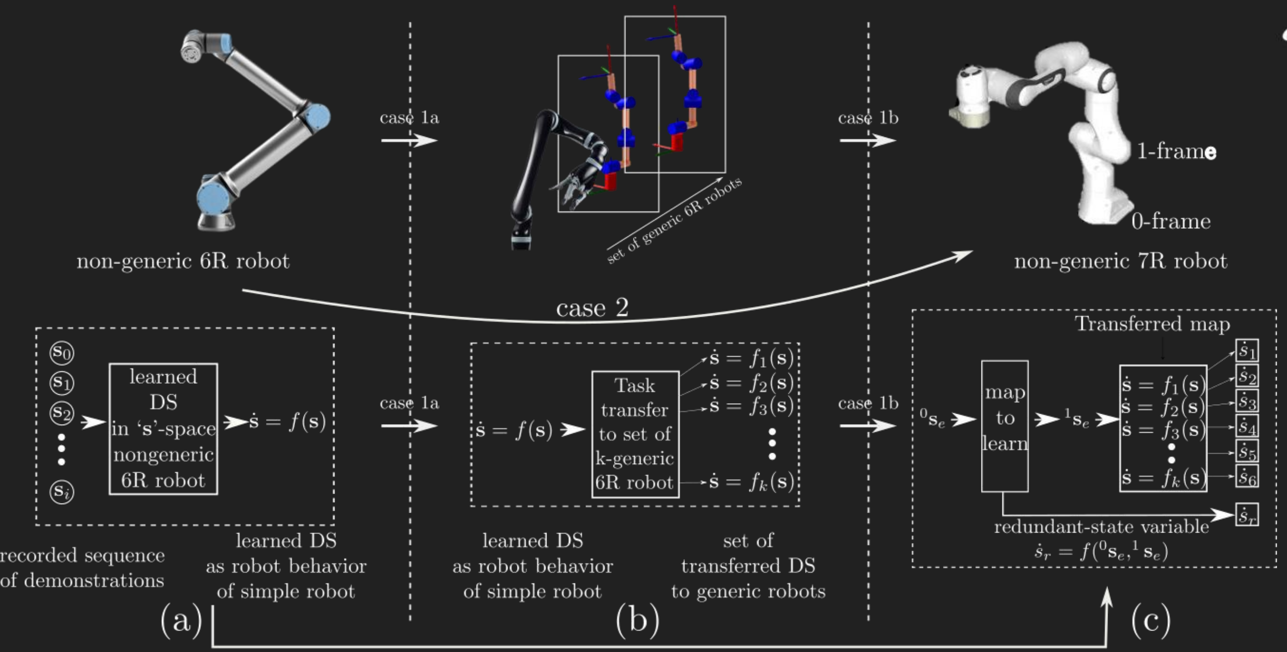
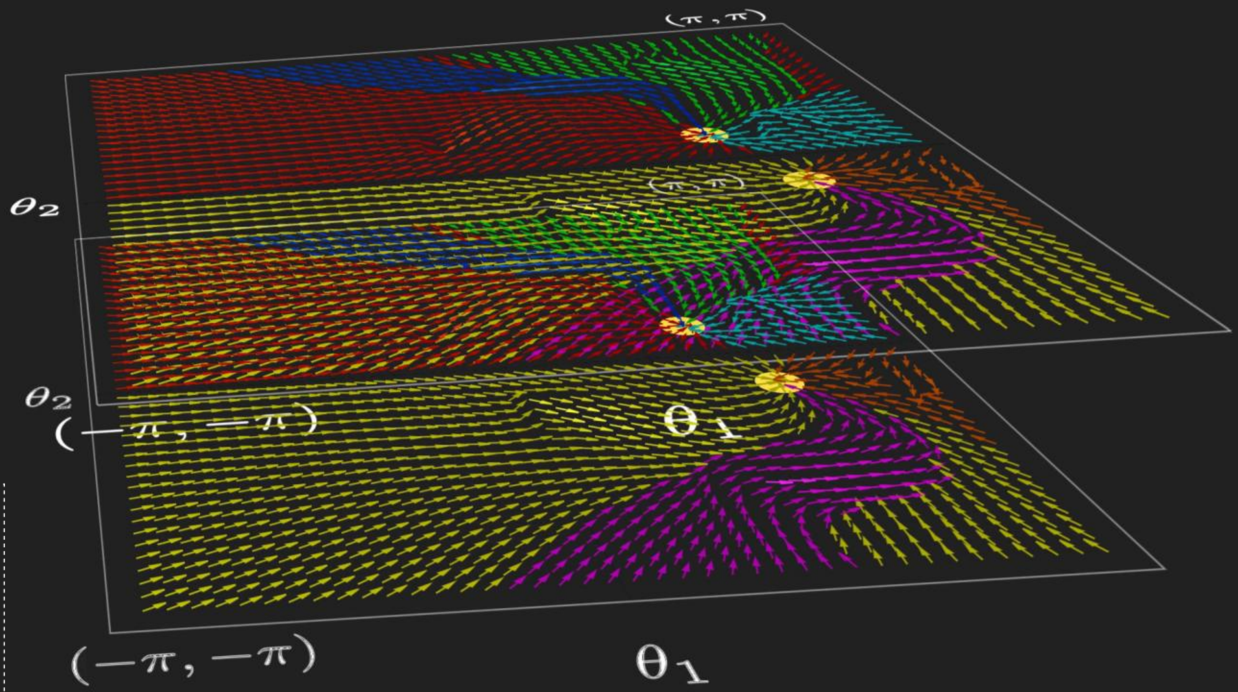




Leveraging kinematic analysis to transfer robot behavior learned from demonstration

Axis 3: Transfer of behaviour





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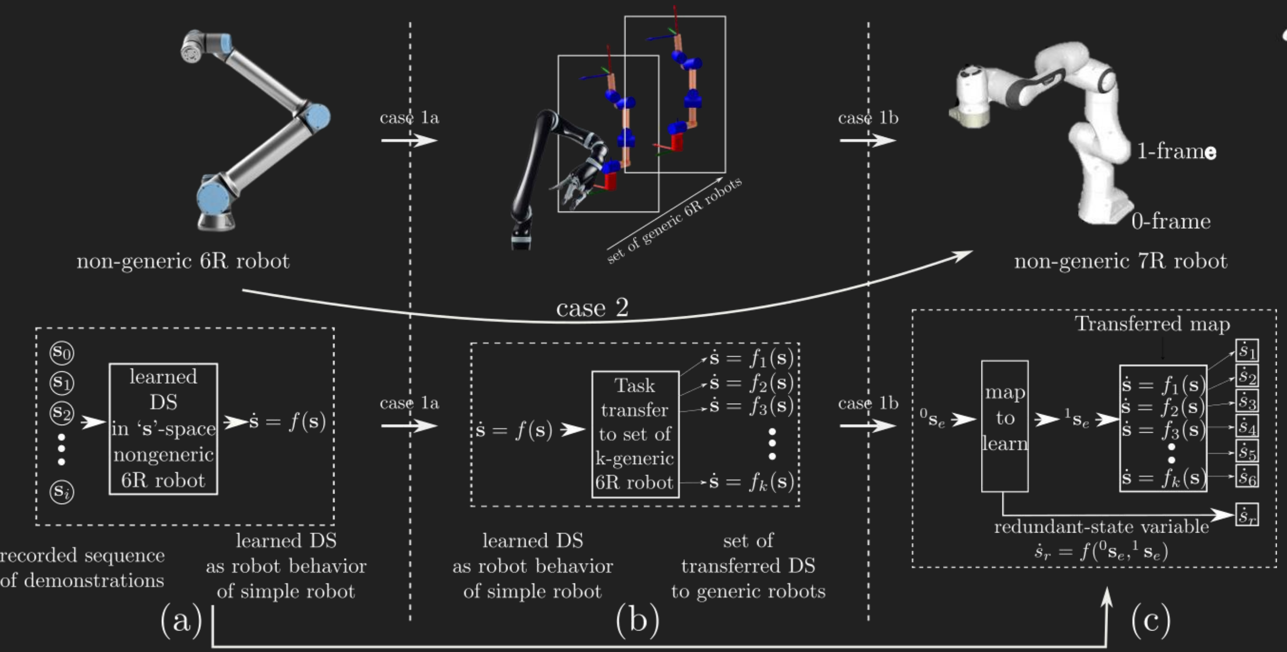
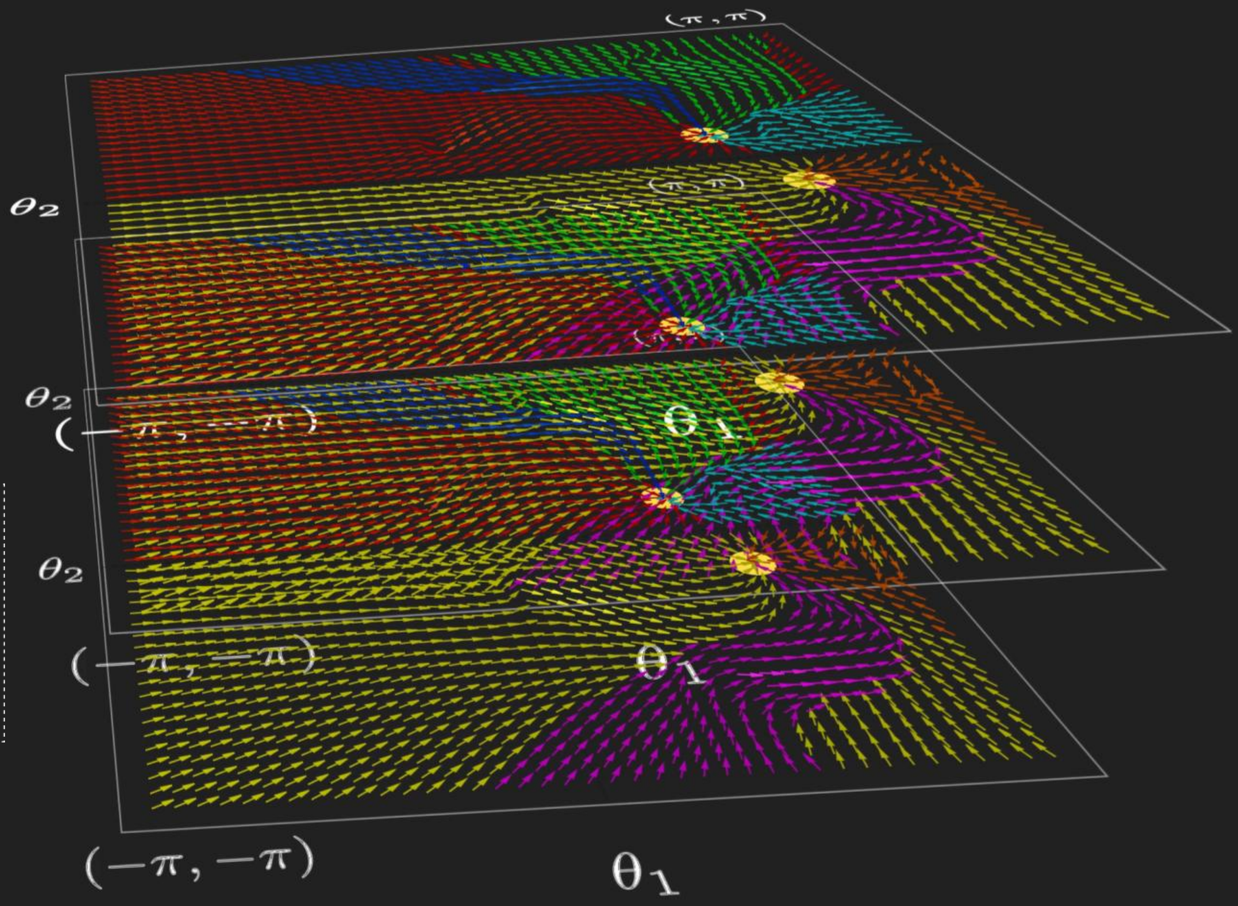
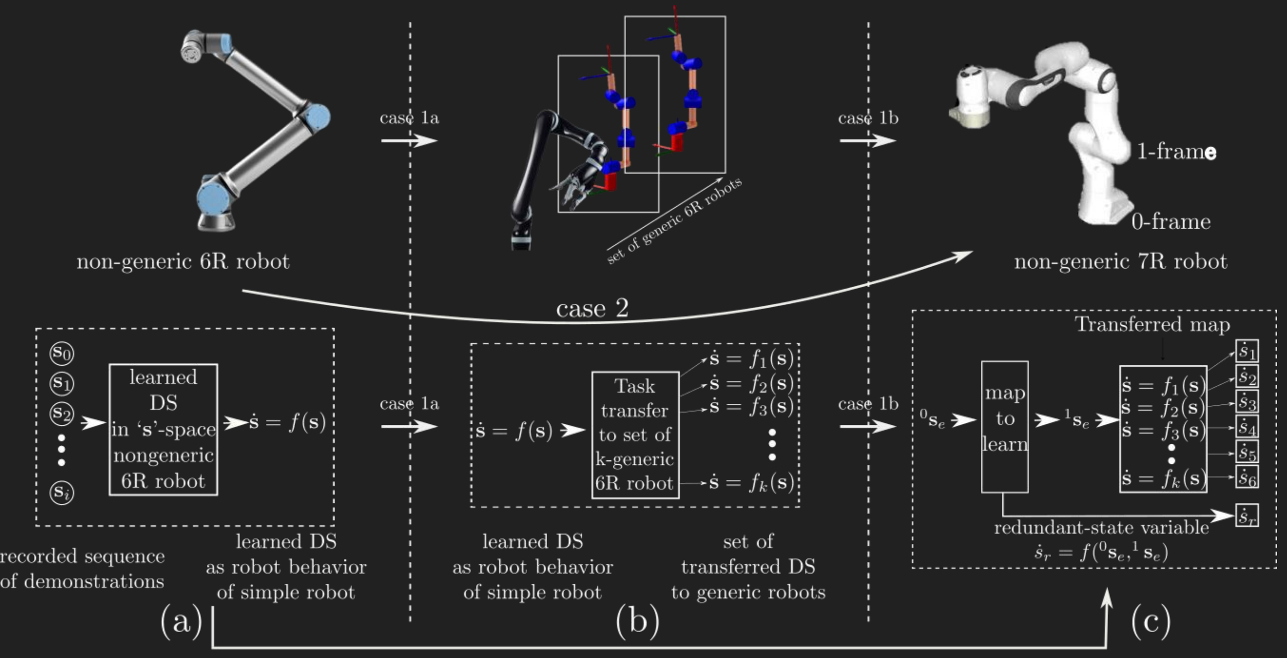
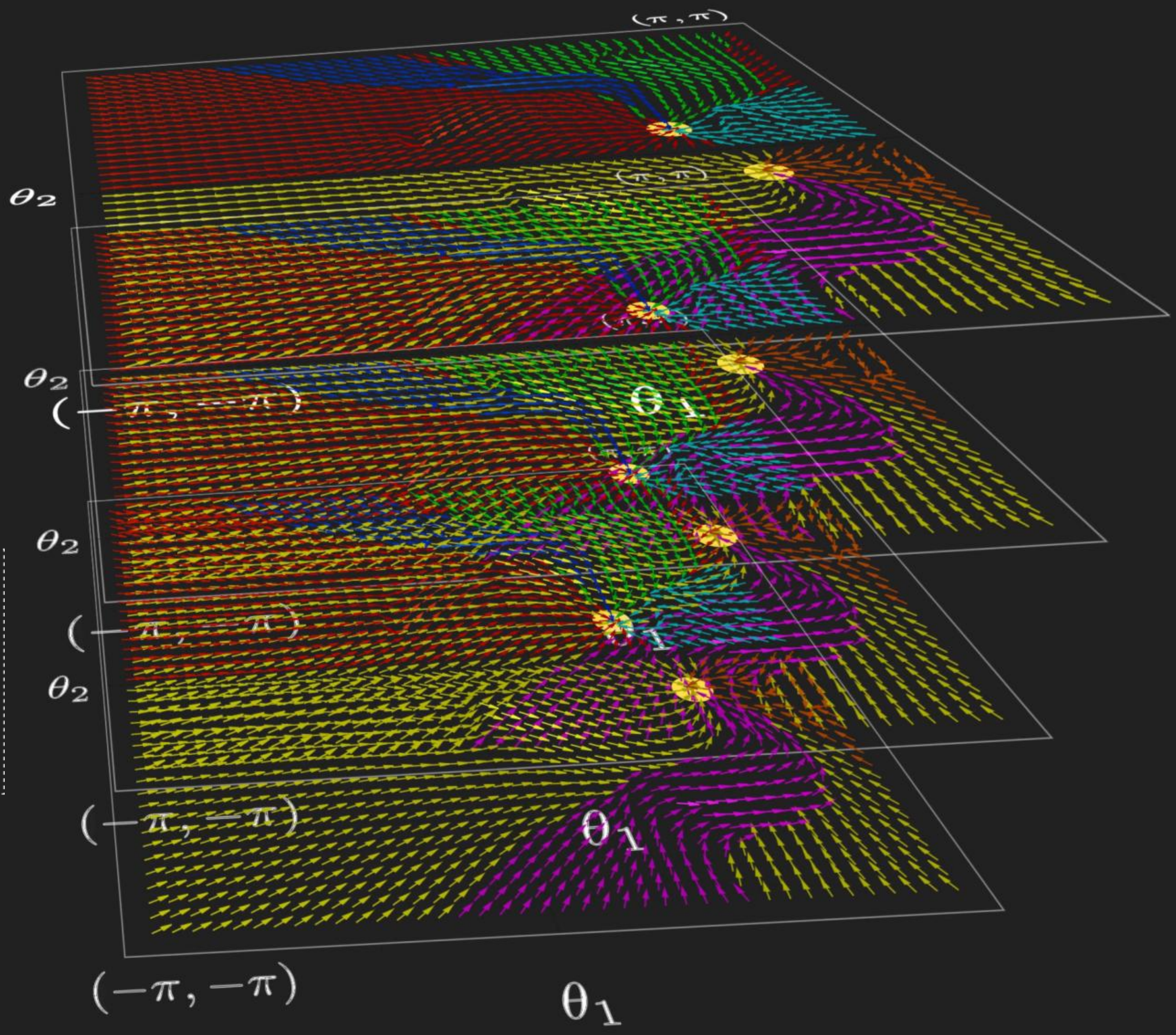




Axis 3: Transfer of behaviour





Leveraging kinematic analysis to transfer robot behavior learned from demonstration

Integration: Team RDH, ICube, Strasbourg

Funding opportunities

1. Programmes et équipements prioritaires de recherche (PEPR)
   A. Robotique organique (O2R) encourages theme of collaborative robotics with focus on safety guarantees.
   B. Funding for equipment, PhD, postdocs and knowledge dissemination
2. ITI – Healthtech :
   A. Funding opportunities specific to medical applications
   B. Funding to support doctoral students

Supervision opportunities

1. Students from INSA Strasbourg
2. Students from Université de Strasbourg

Integration: Team RDH, ICube, Strasbourg

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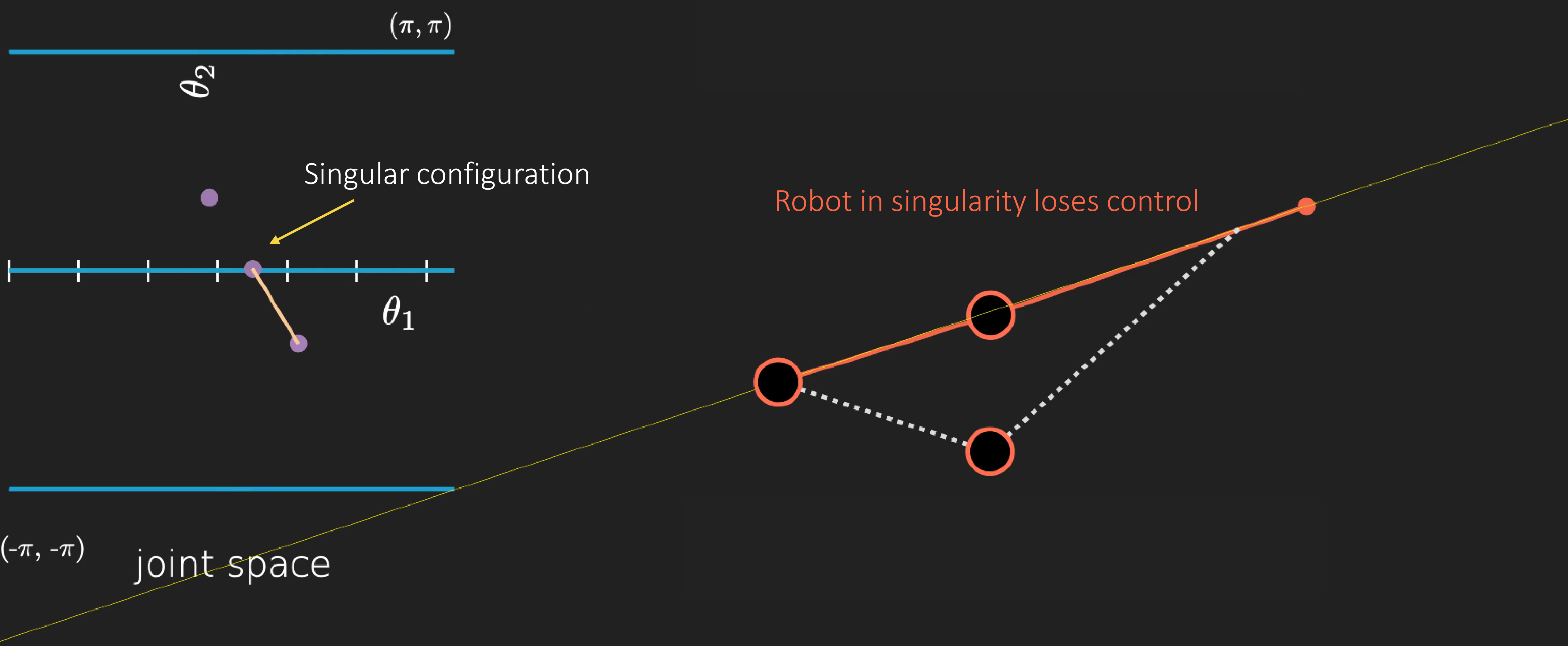
   B. Funding for equipment, PhD, postdocs and knowledge dissemination
   C. Project AS2 is currently led by Philippe Souères (Robot motion with physical interactions and social adaptation)

Supervision opportunities

1. Students from INSA Toulouse
2. Students from Université de Toulouse

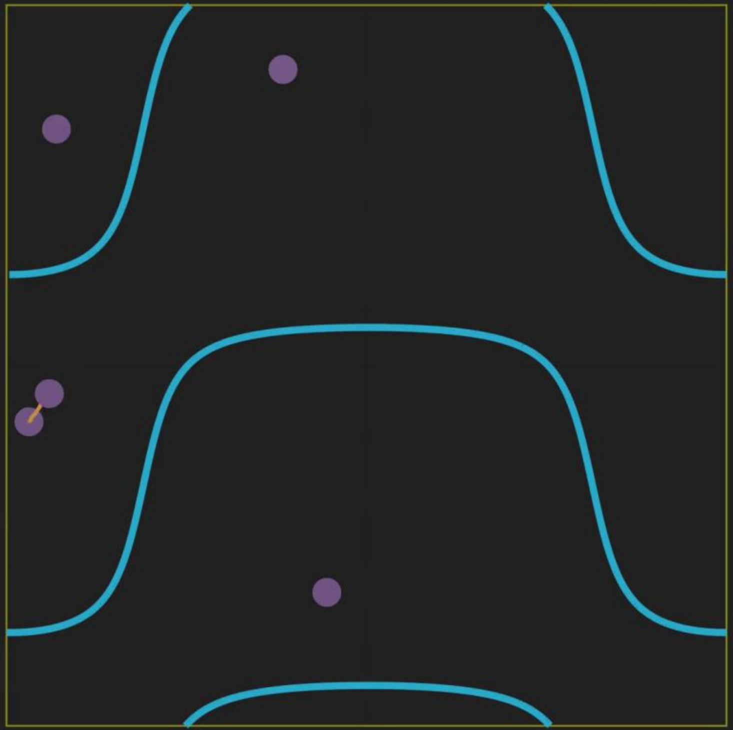
Research activity: Doctorate (2020 - 2023)



Leveraging kinematic analysis to transfer robot behavior learned from demonstration

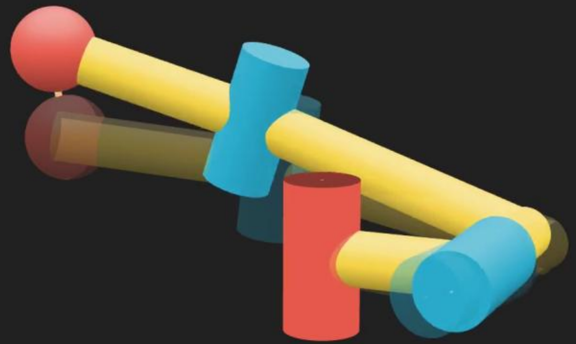
Robot changing its inverse kinematic solution without crossing singularity!

(π, π)

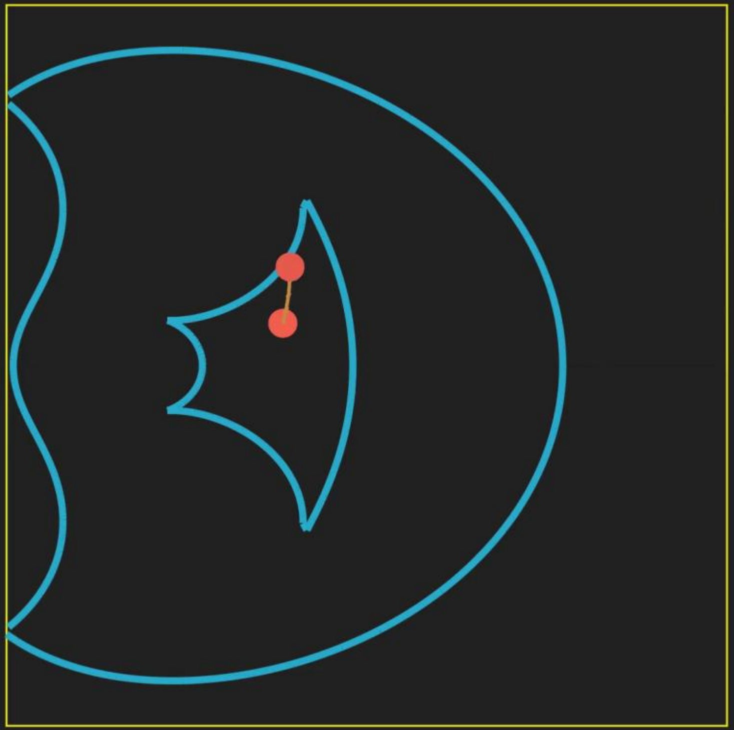


$(-\pi, -\pi)$

joint space



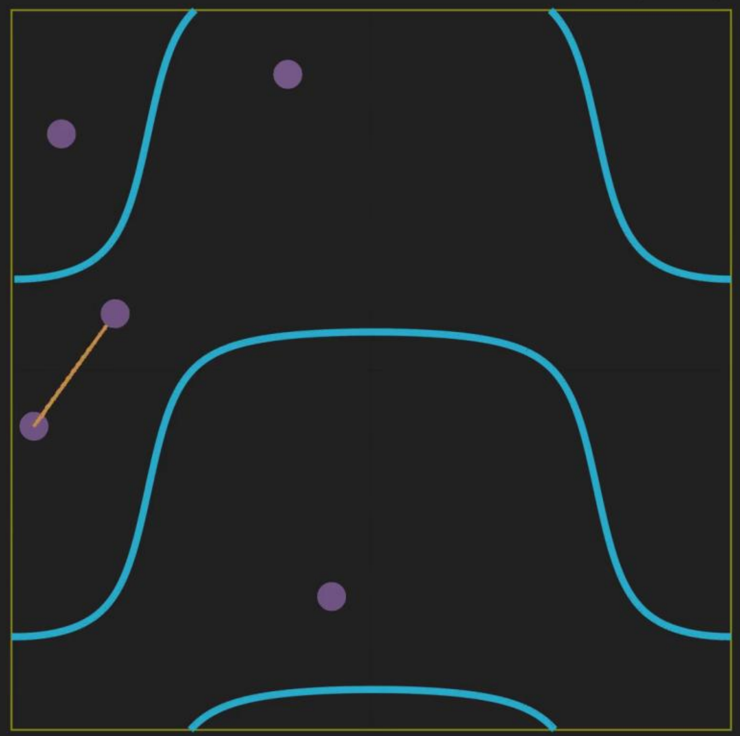
z



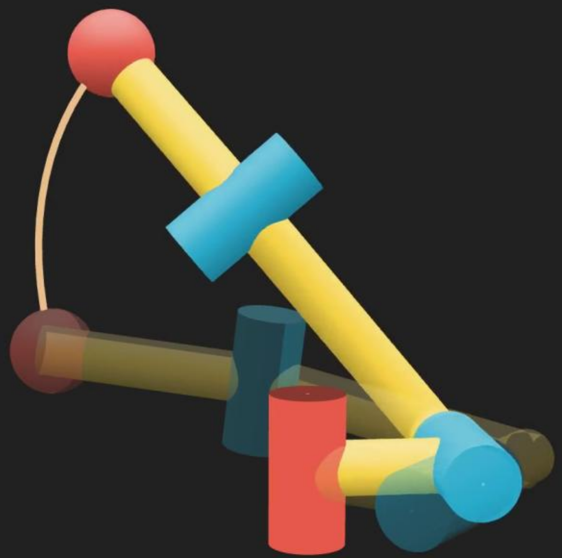
ρ

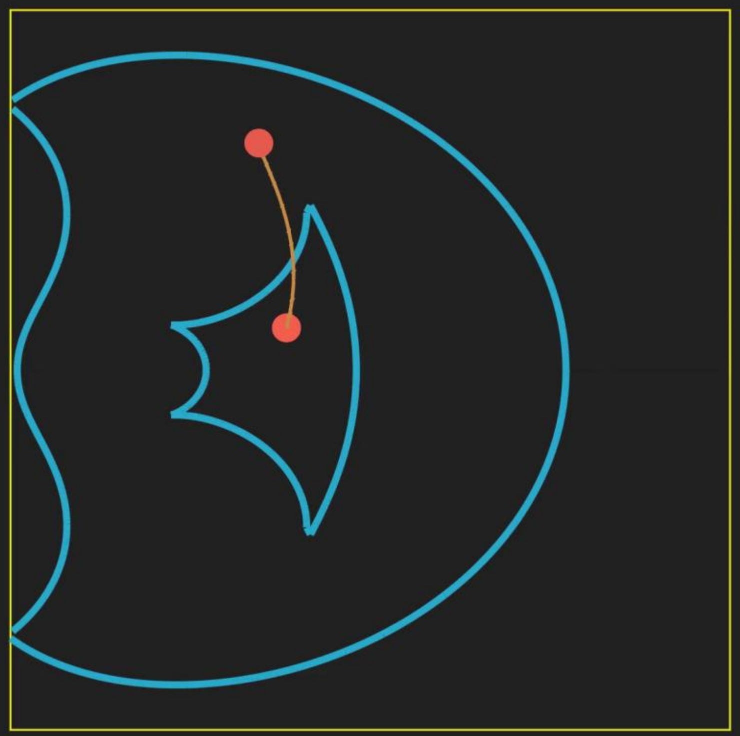
work space projection on ρ-z plane ($\rho = \sqrt{x^2 + y^2}$)

Robot changing its inverse kinematic solution without crossing singularity!



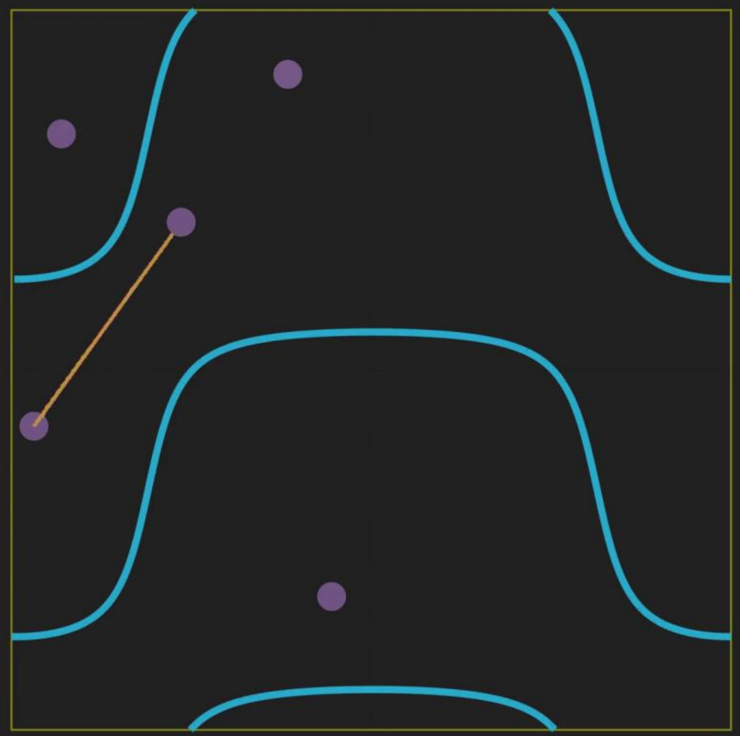
joint space



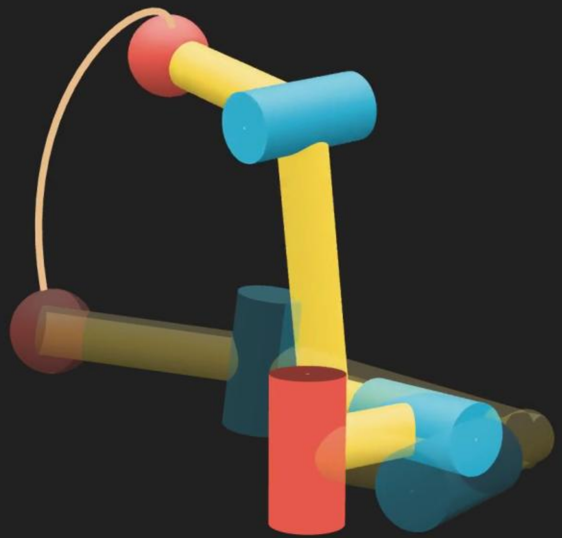


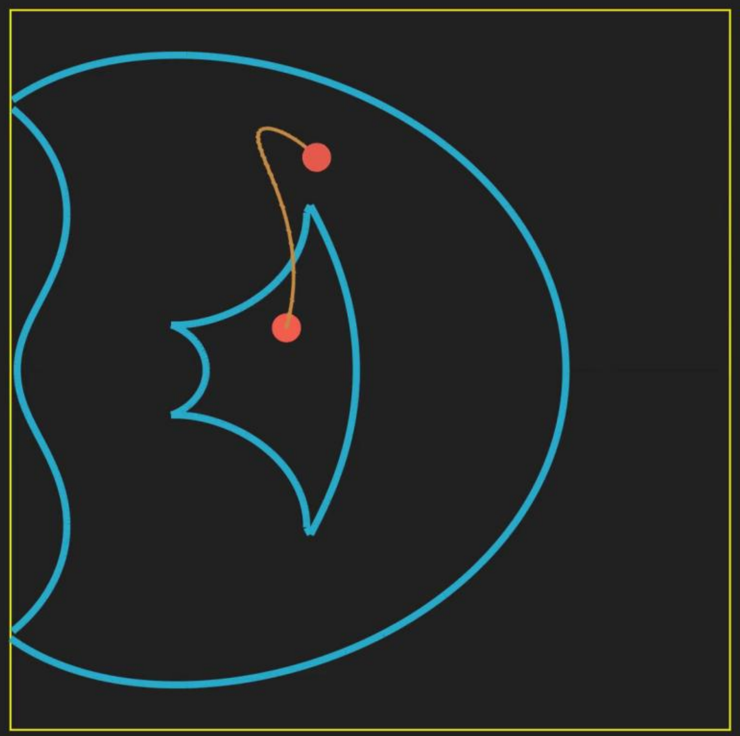
work space projection on ρ-z plane ($\rho = \sqrt{x^2 + y^2}$)

Robot changing its inverse kinematic solution without crossing singularity!



joint space

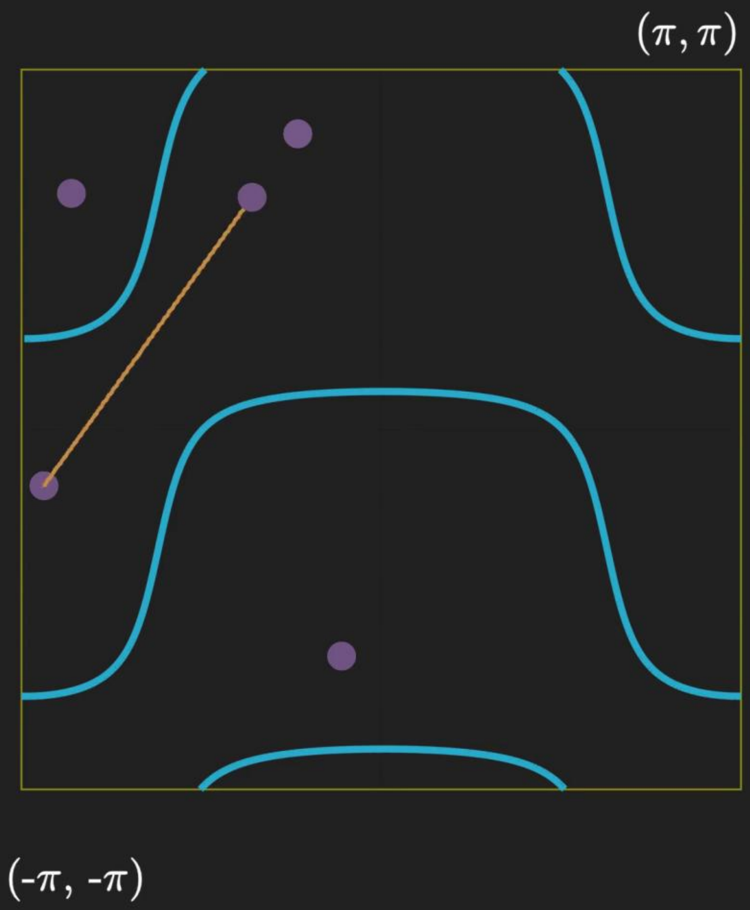




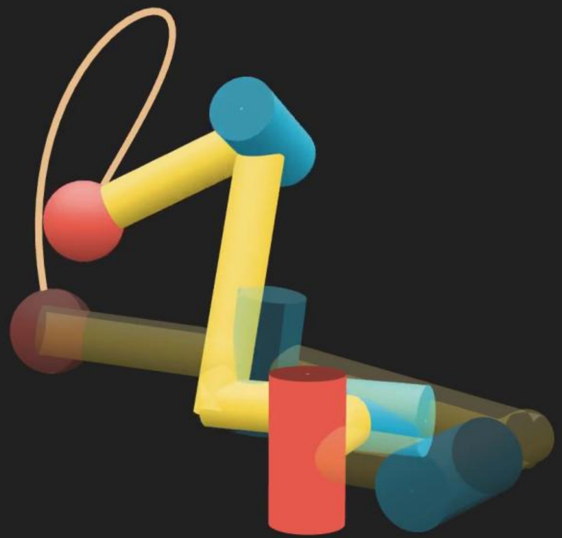
work space projection on ρ-z plane

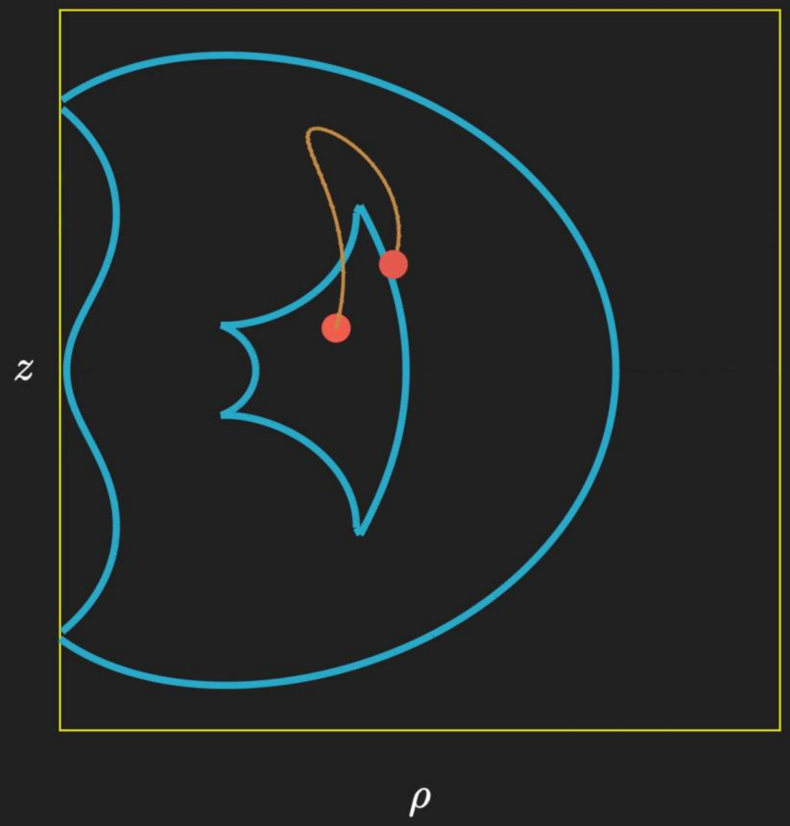
$(\rho = \sqrt{x^2 + y^2})$

Robot changing its inverse kinematic solution without crossing singularity!



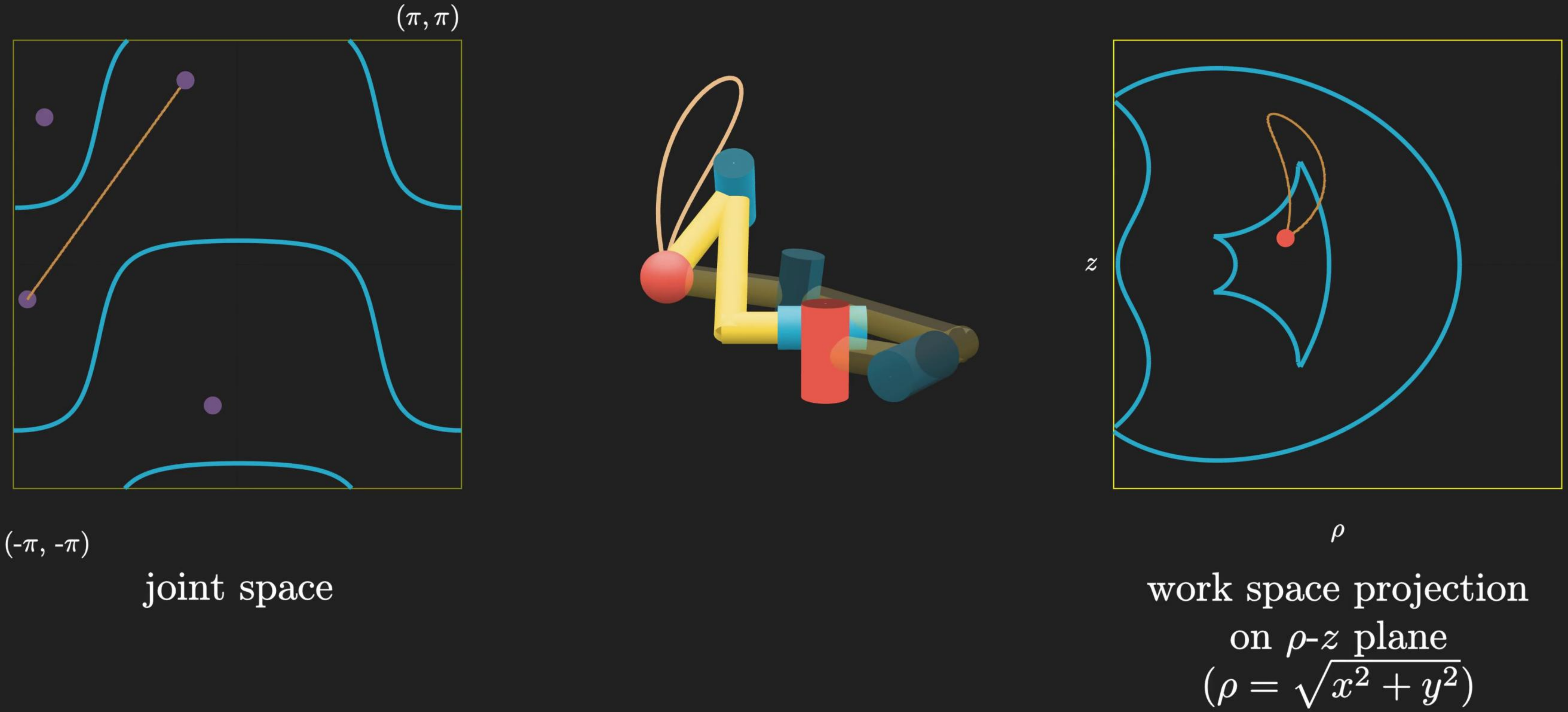
joint space



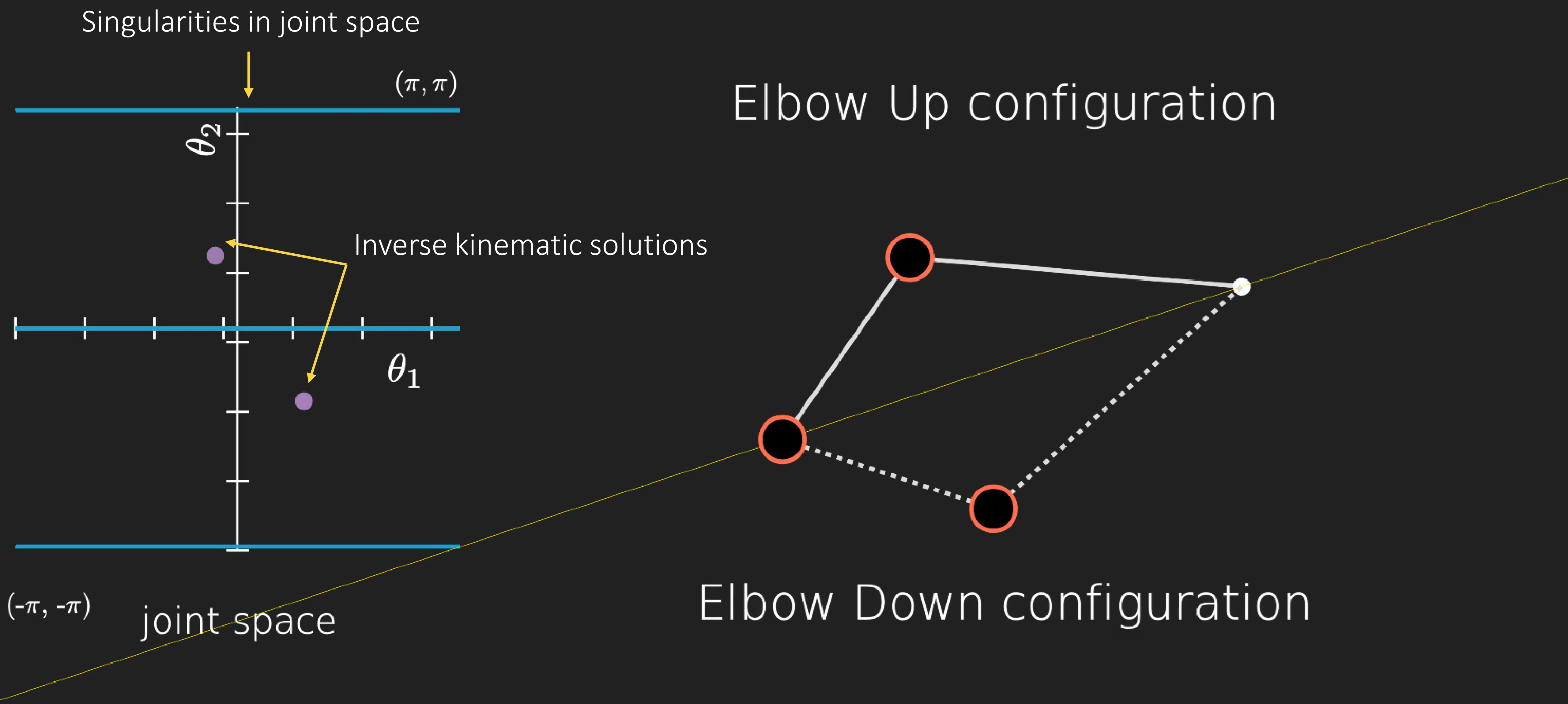


work space projection on ρ-z plane ($\rho = \sqrt{x^2 + y^2}$)

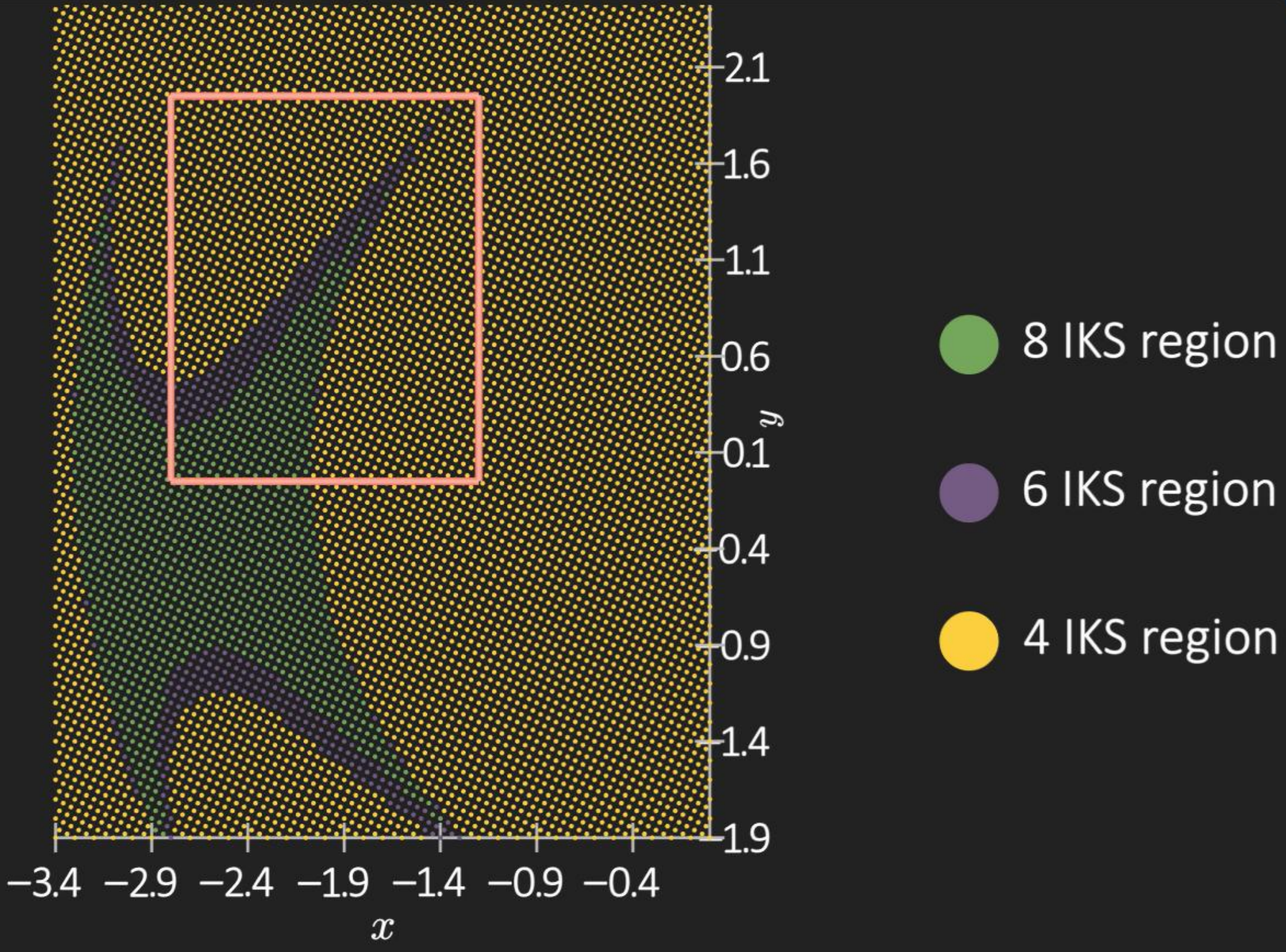
Robot changing its inverse kinematic solution without crossing singularity!



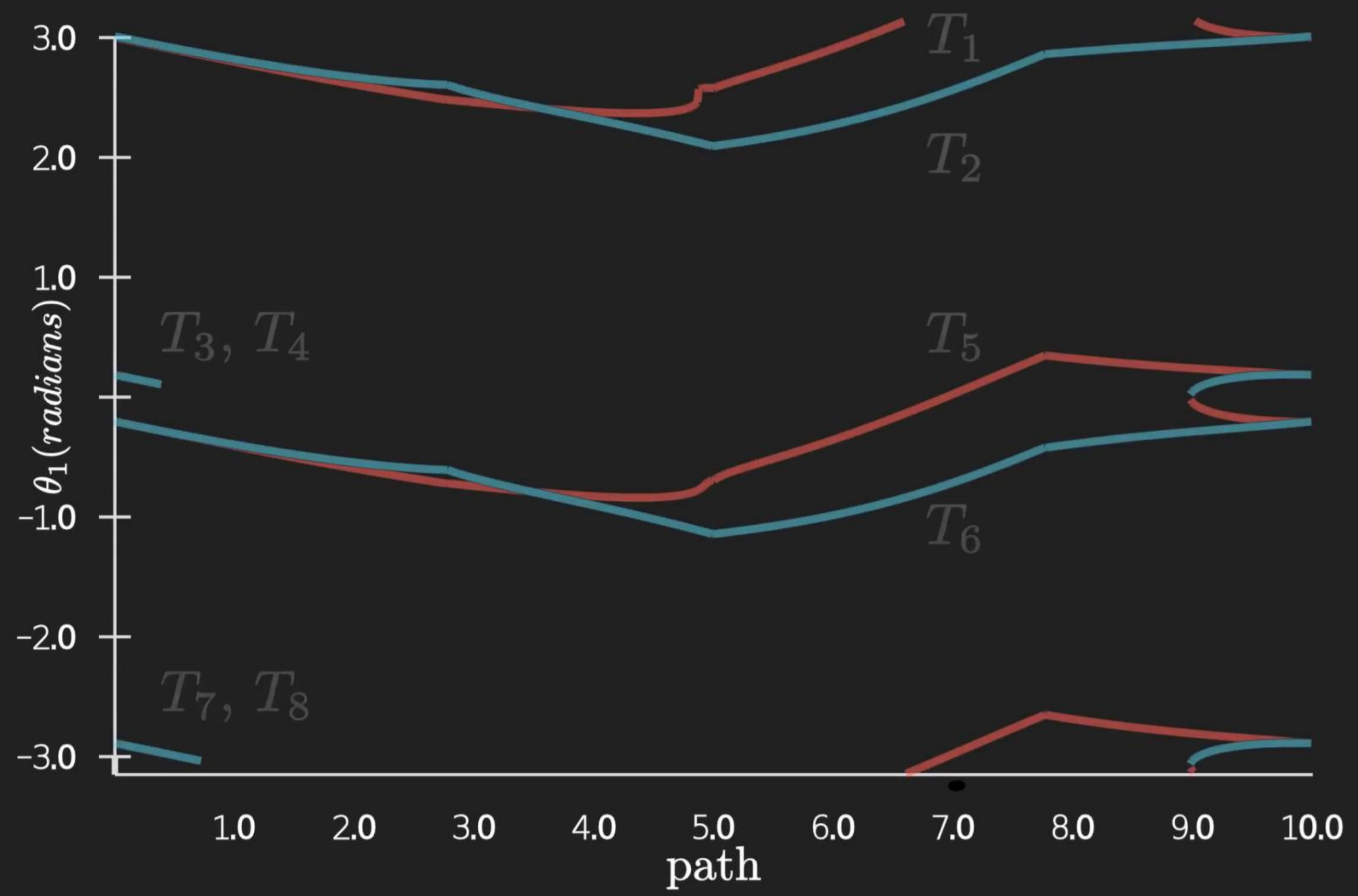
Research activity: Doctorate (2020 - 2023)

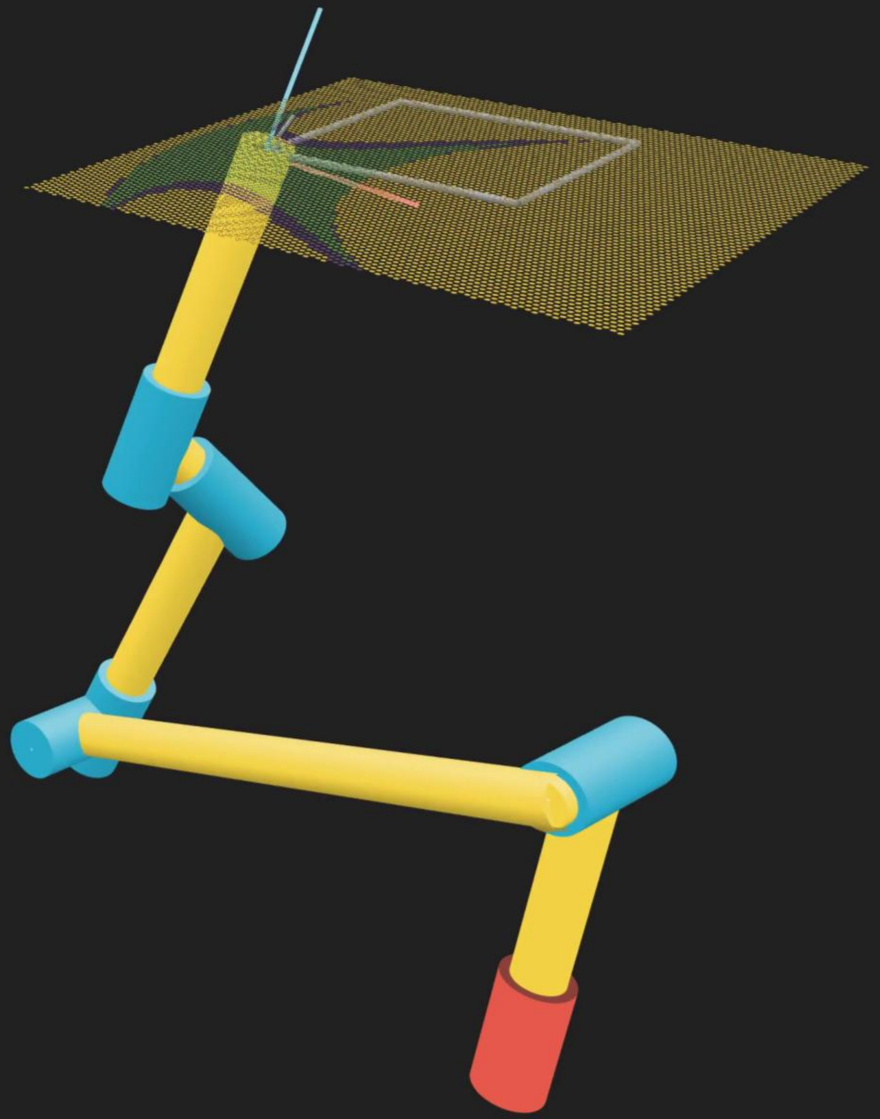


Research activity: Doctorate (2020 - 2023)



Eight possible paths to follow the given loop





Axis 1: Learning behaviour from demonstration

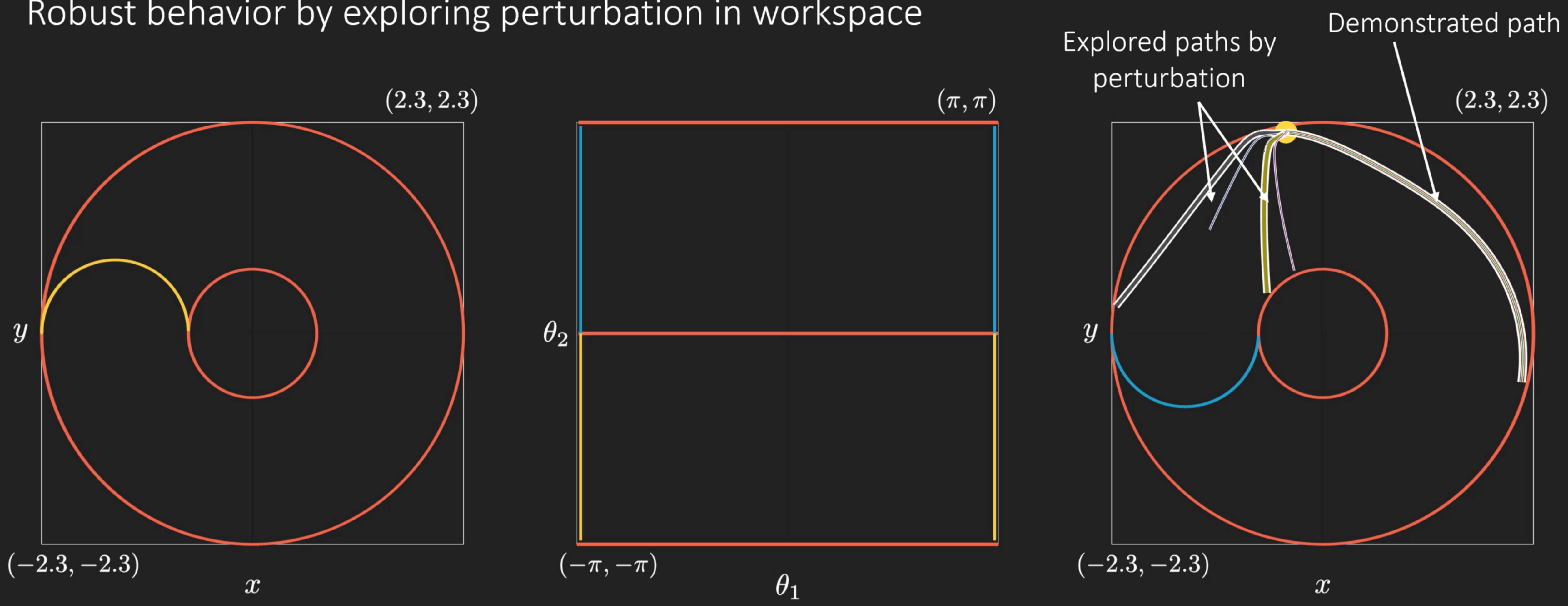
Motion planning in the workspace is preferred as the demonstration is performed in task space

Motion planning in workspace	Motion planning in joint space
Hard to derive singularities in workspace --	Smooth singularities +
Joint limits are dependent on aspect in which path is to be tracked --	Joint limits are easy to handle +
Space is not homogenous as we go from 3R to 6R (position + orientation) --	Homogenous space as the degrees of freedom increases +
The behavior is native to the space of demonstration +	Multiple regions exist that can map the same behavior --
The behavior upon perturbation is well captured +	Slight perturbations may cause large change in path --

Learn behavior in joint space by exploring paths upon perturbation in workspace

Axis 1: Learning behaviour from demonstration

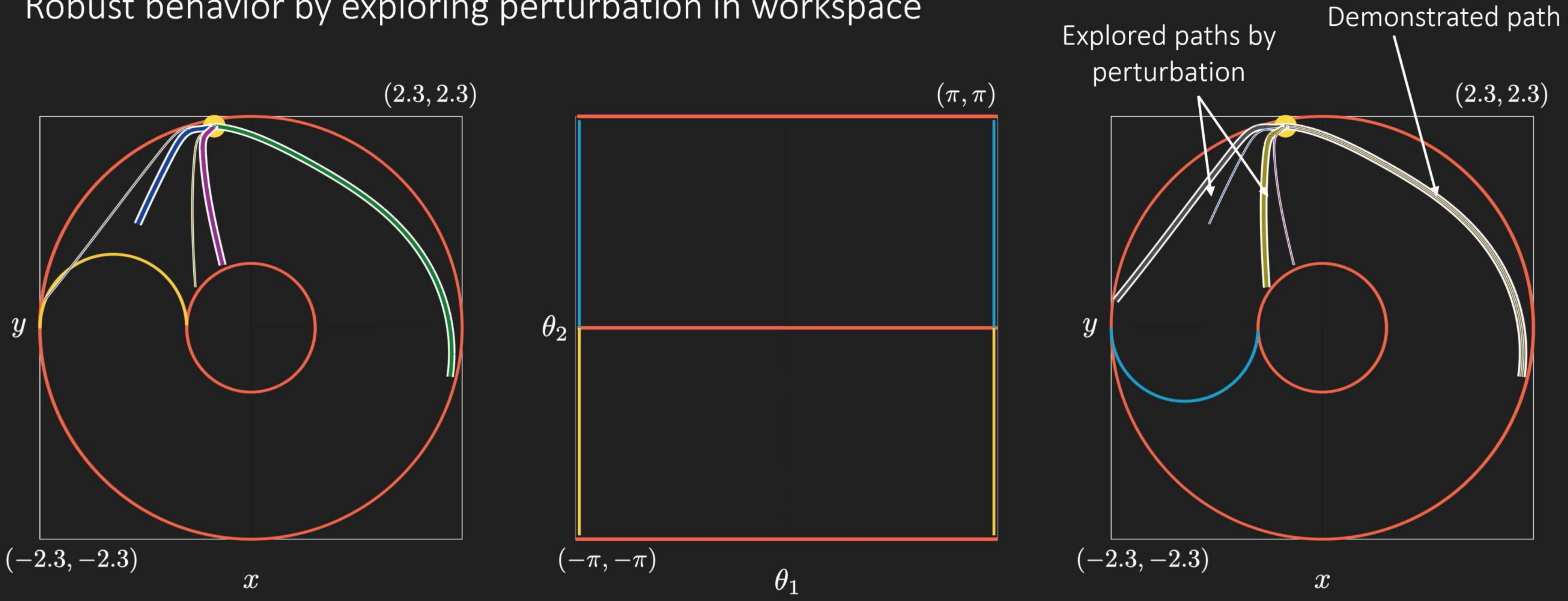
Robust behavior by exploring perturbation in workspace



Demonstartion recorded in workspace

Axis 1: Learning behaviour from demonstration

Robust behavior by exploring perturbation in workspace

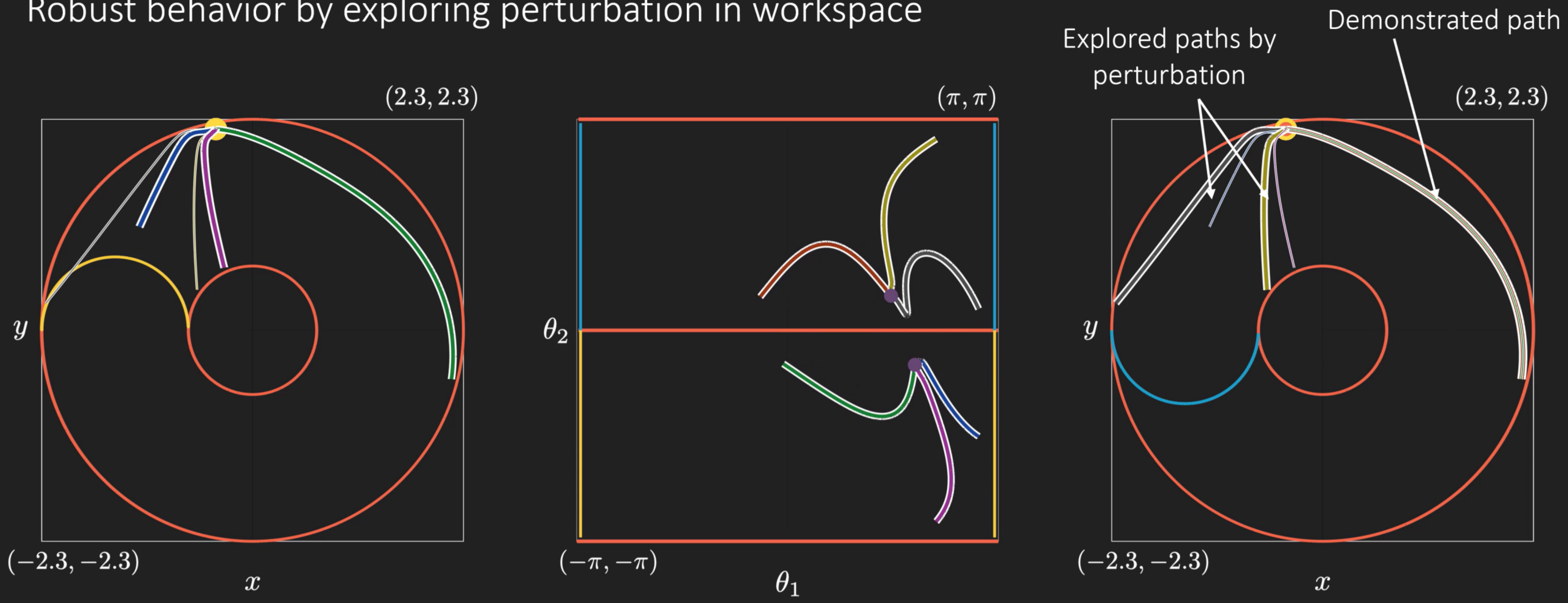


Demonstartion recorded in workspace for aspect 2

Demonstartion recorded in workspace

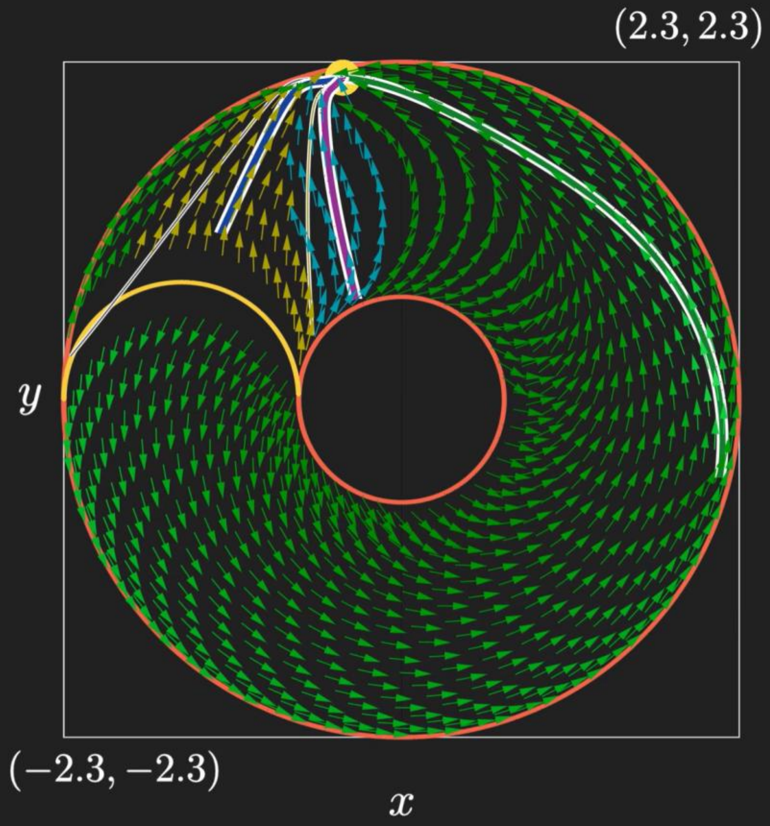
Axis 1: Learning behaviour from demonstration

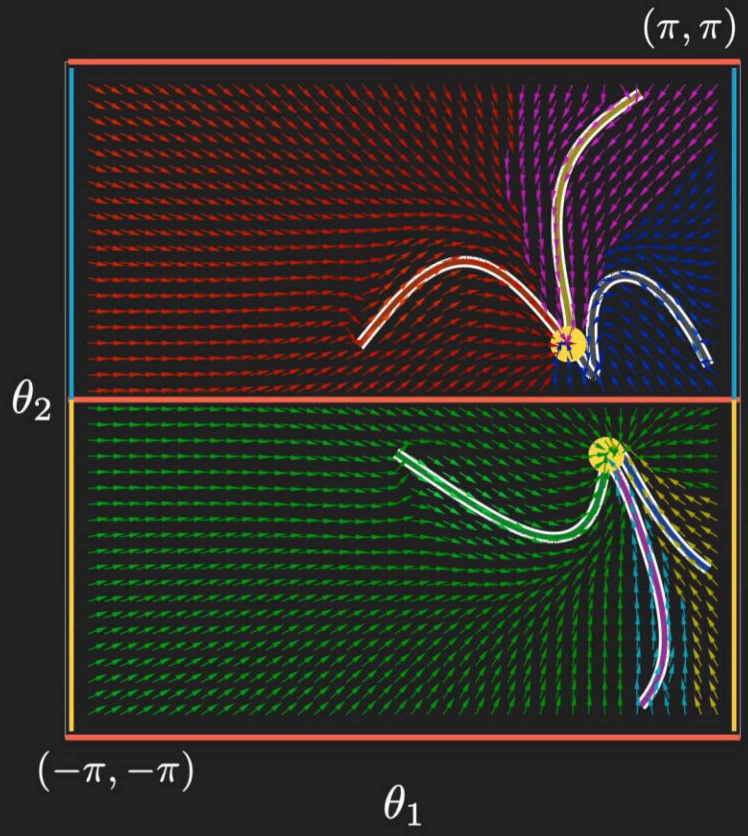
Robust behavior by exploring perturbation in workspace



Axis 1: Learning behaviour from demonstration

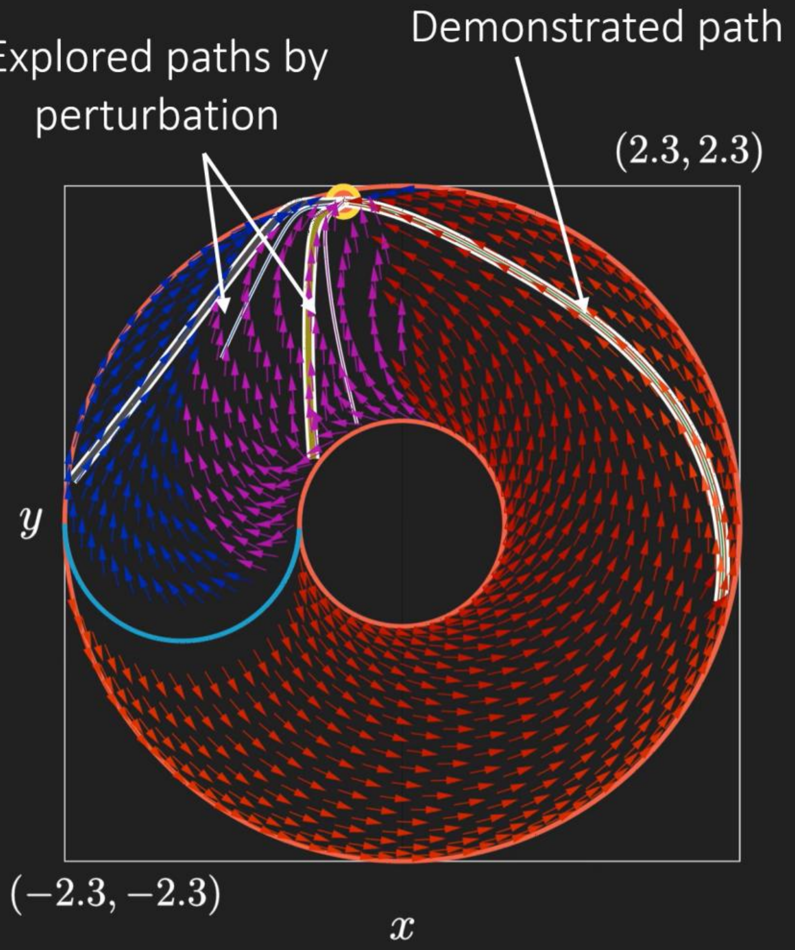
Robust behavior by exploring perturbation in workspace



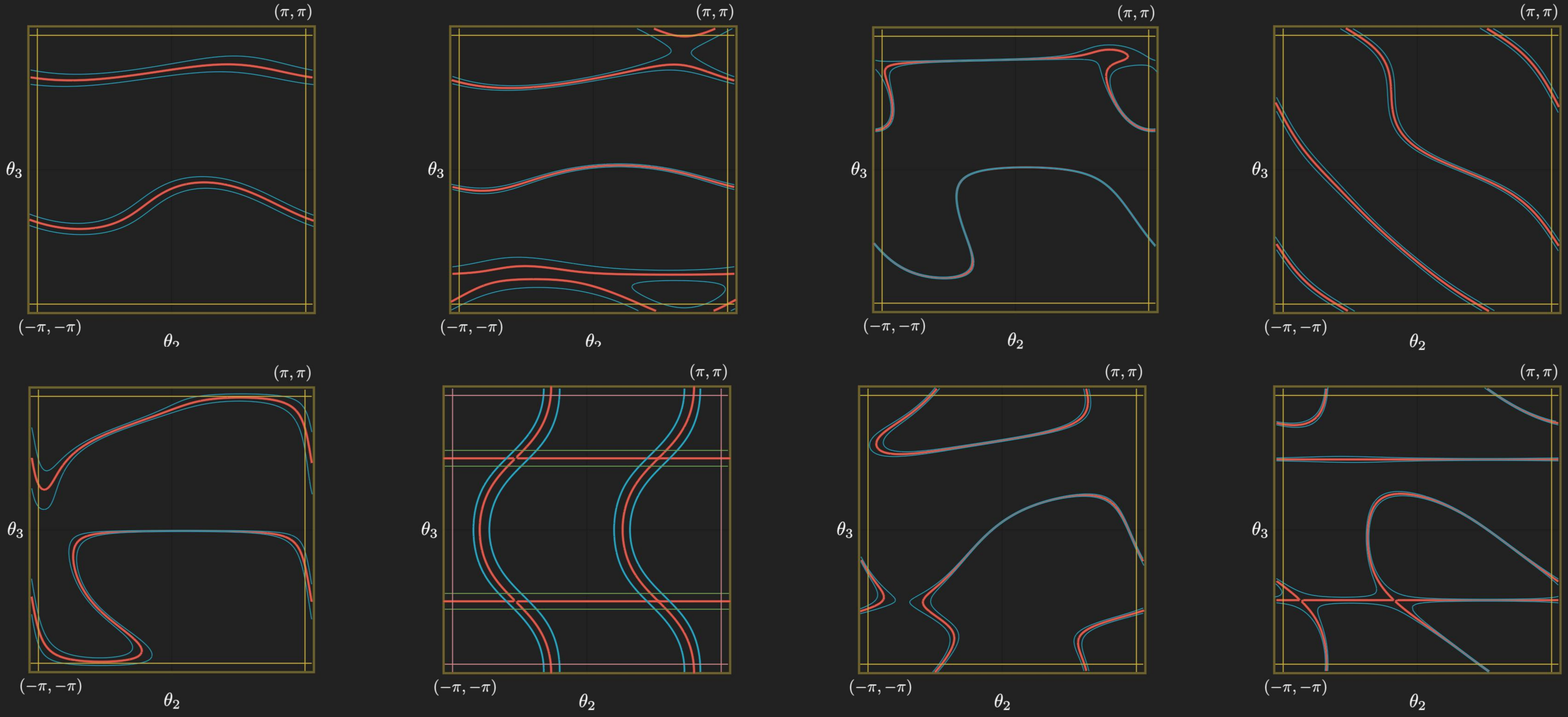


Demonstration in joint space

Generalization in joint space



Axis 2: Kinematic analysis

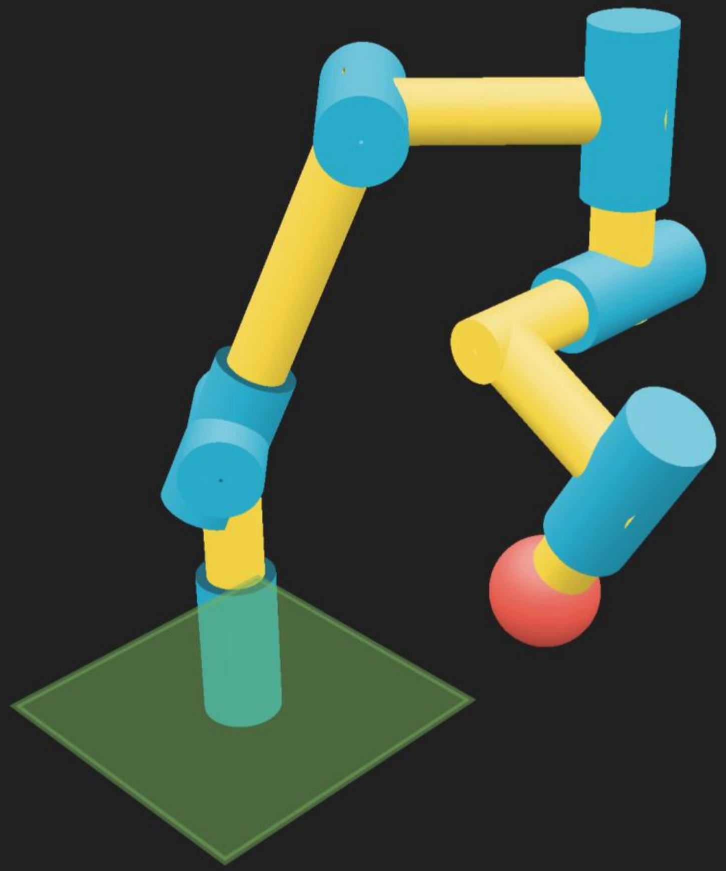


Different types of joint space singularities in 3R robots

Axis 2: Kinematic analysis

7R robots have singularities in 4 dimensions + 1 parameter

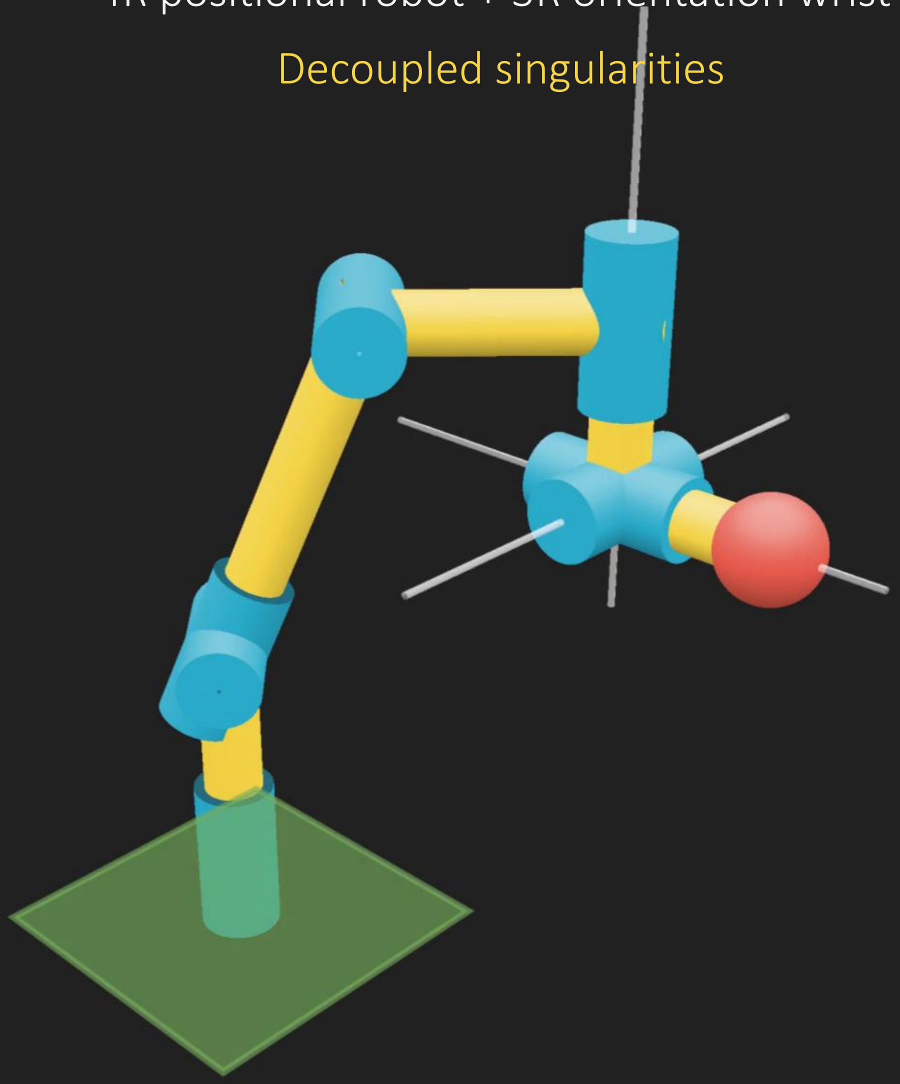
Impossible to visualize



Generic 7R robot

4R positional robot + 3R orientation wrist

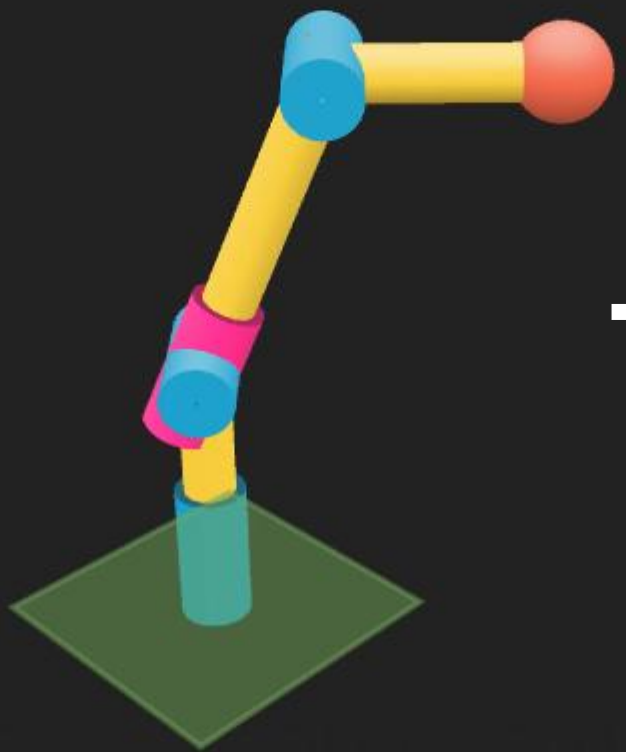
Decoupled singularities



Axis 2: Kinematic analysis

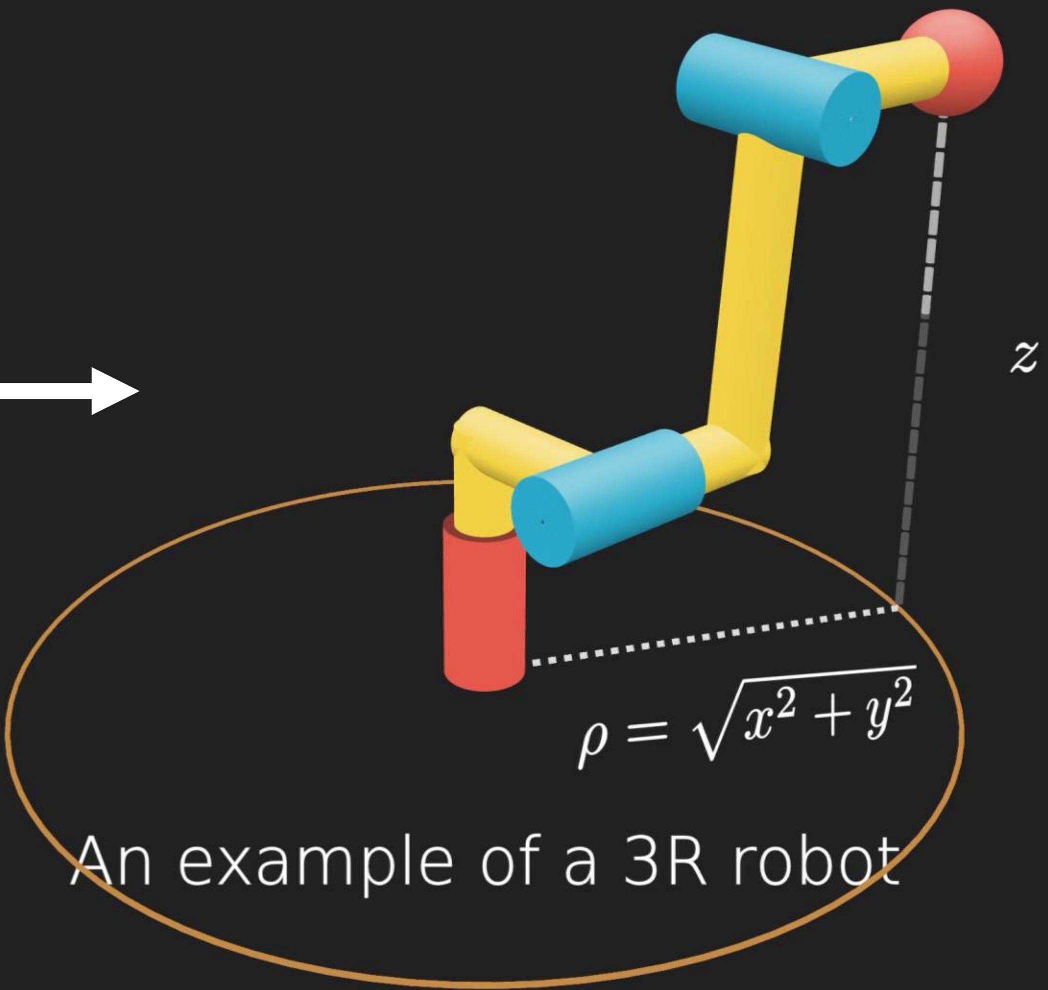
4R robot => 3R positional robot+ 1 parameter

Visualizable singularities!



3R positional robot => reduced to only 2 parameters

Singularities plot in 2D plane

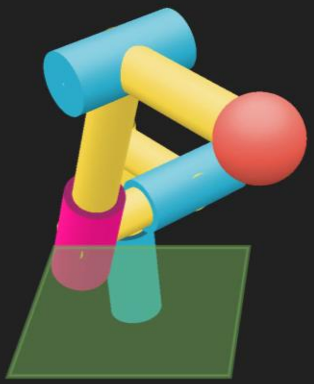


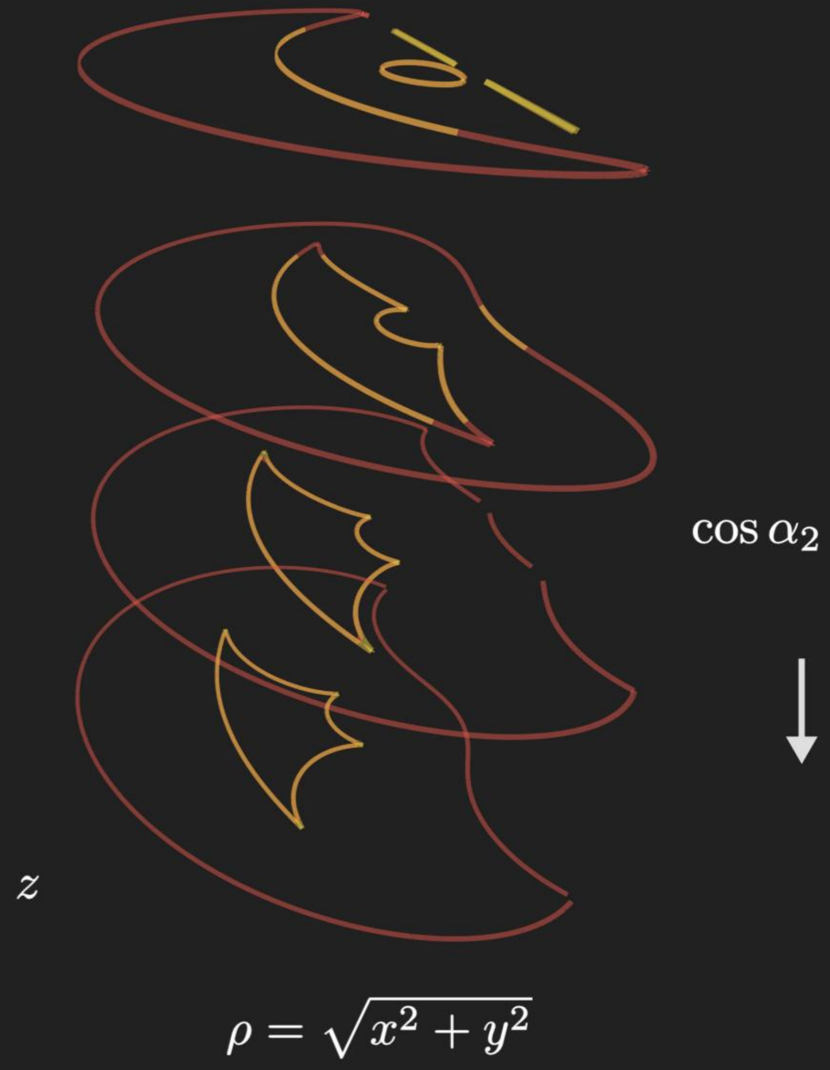
$$\theta_1 \notin \det(\mathbf{J})$$

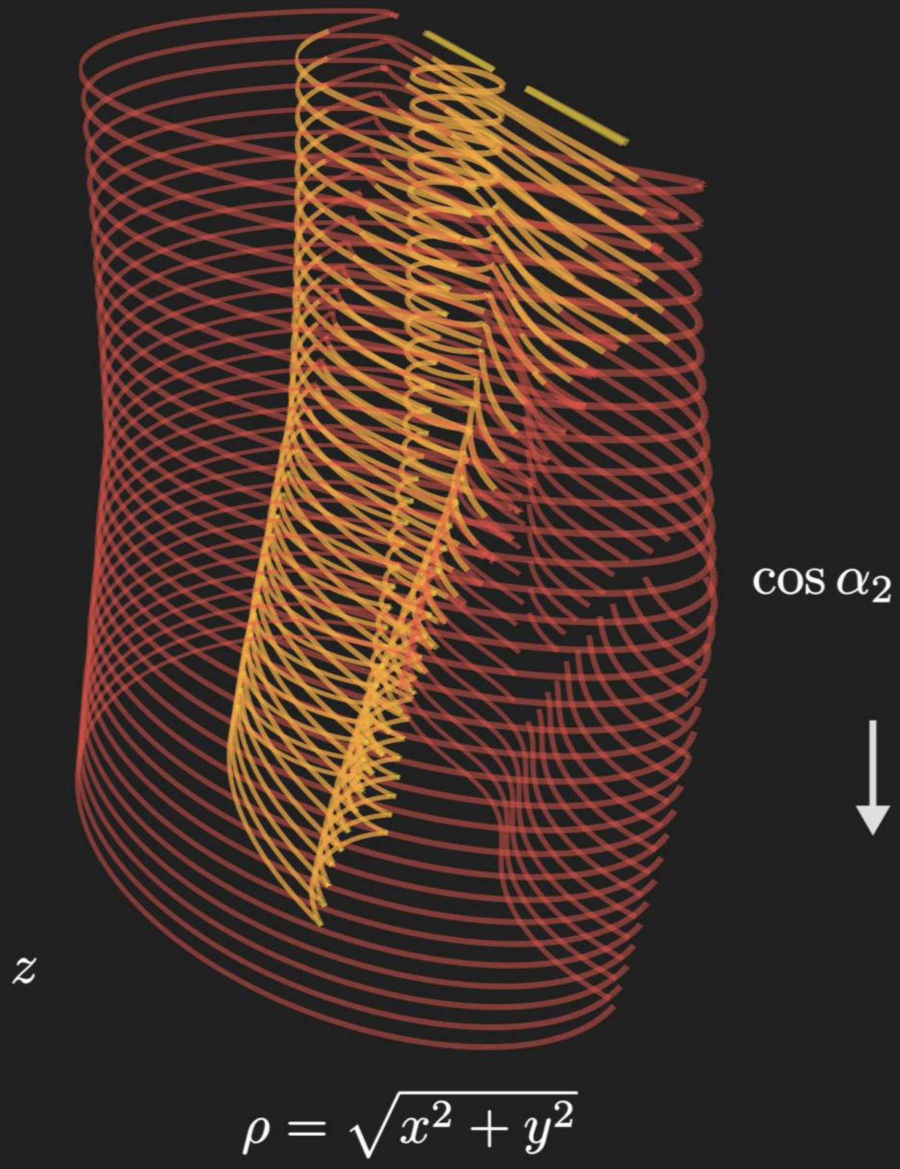
singularity depends only on $\theta_2, \theta_3 \in \mathbb{T}^2$

Axis 2: Kinematic analysis

What happens when a 7R robot is cuspidal?



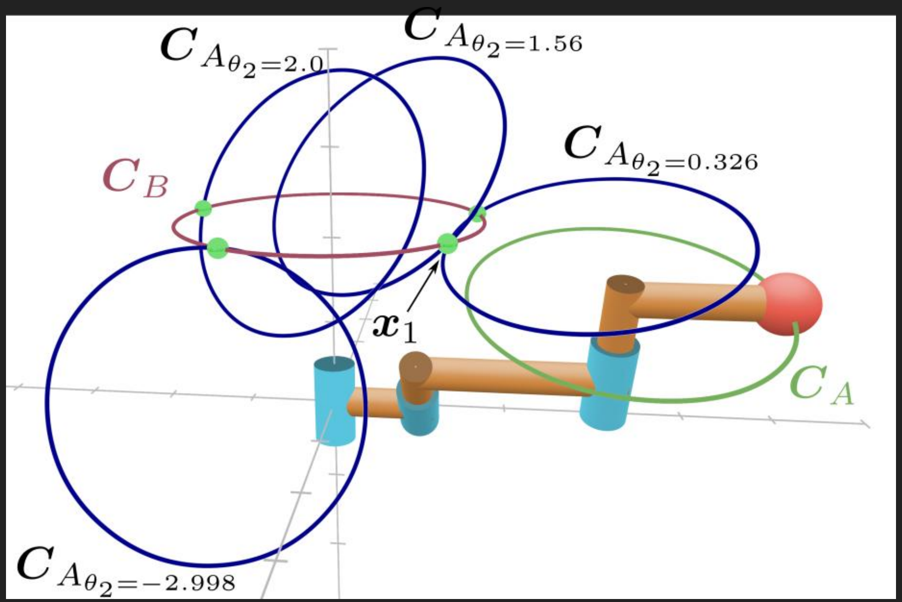




Axis 2: Kinematic analysis

What is Conformal Geometric Algebra?

- CGA is a framework to represent and manipulate:
  - Points, lines, planes, circles, spheres
  - Rigid & conformal transformations (rotate, translate, scale, invert)
- Embeds 3D space into 5D using:
- Two extra basis vectors: e_0 and e_∞
- Combines position + metric info
- Enables distance, angle, and intersection as algebraic operations



Inverse kinematics using CGA

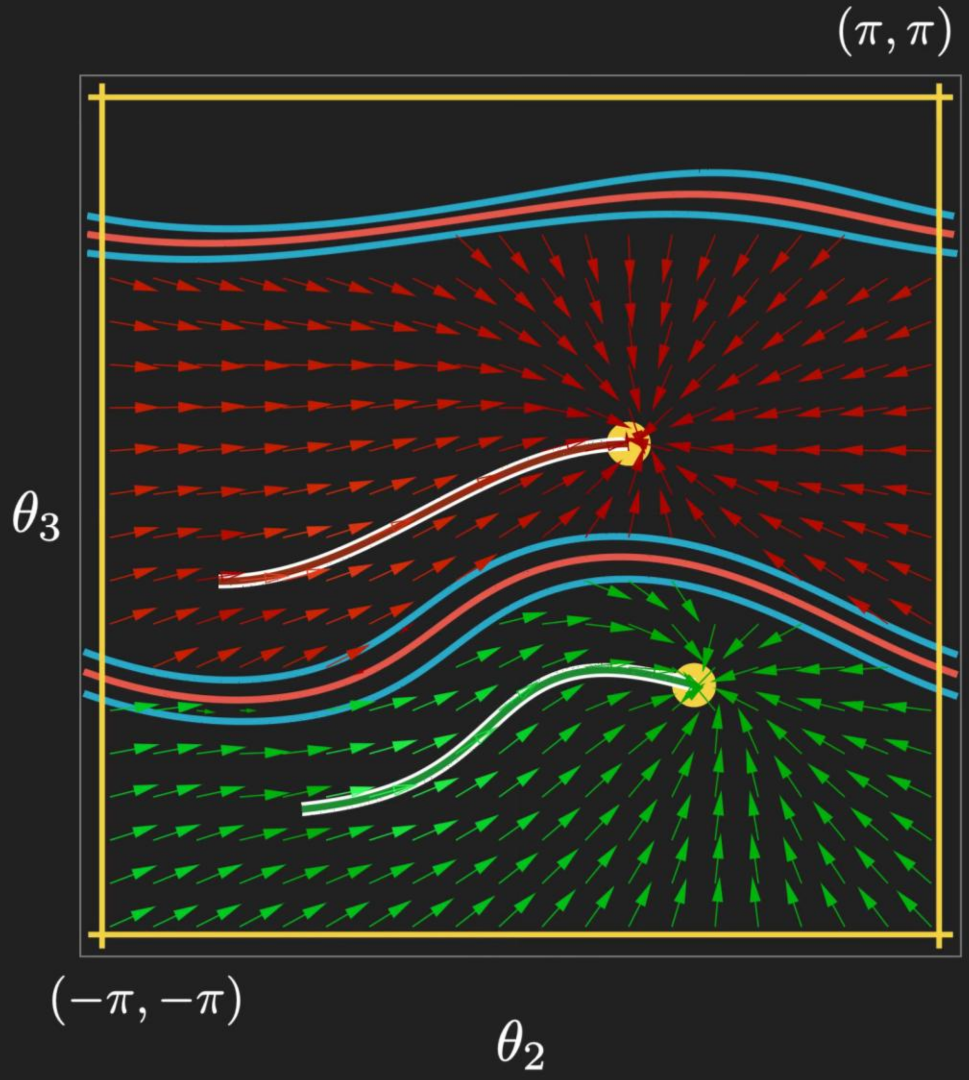
$$X = \mathbf{x} + \frac{1}{2}\|\mathbf{x}\|^2 e_\infty + e_0$$

Conformal embedding of a point

CGA primitives	Direct/primal (OPNS)	Dual (OPNS)
Point $\boldsymbol{p}$	$\boldsymbol{x}$	$\boldsymbol{x}$
Point pair $\boldsymbol{A}$	$\boldsymbol{p}_1 \wedge \boldsymbol{p}_2$	$\boldsymbol{S}_1 \vee \boldsymbol{S}_2 \vee \boldsymbol{S}_3$
Sphere $\boldsymbol{S}$	$\boldsymbol{p}_1 \wedge \boldsymbol{p}_2 \wedge \boldsymbol{p}_3 \wedge \boldsymbol{p}_4$	$\boldsymbol{p}_S - \frac{1}{2}r^2\boldsymbol{e}_\infty$
Plane $\boldsymbol{E}$	$\boldsymbol{p}_1 \wedge \boldsymbol{p}_2 \wedge \boldsymbol{p}_3 \wedge \boldsymbol{e}_\infty$	$\boldsymbol{n} + d\boldsymbol{e}_\infty$
Line $\boldsymbol{L}$	$\boldsymbol{p}_1 \wedge \boldsymbol{p}_2 \wedge \boldsymbol{e}_\infty$	$\boldsymbol{E}_1 \vee \boldsymbol{E}_2$
Circle $\boldsymbol{C}$	$\boldsymbol{p}_1 \wedge \boldsymbol{p}_2 \wedge \boldsymbol{p}_3$	$\boldsymbol{S}_1 \vee \boldsymbol{S}_2$ or $\boldsymbol{S}_1 \vee \boldsymbol{E}_1$

Axis 1: Learning behaviour from demonstartion

Respecting constraints for a generic 3R robot



Singularities in joint space