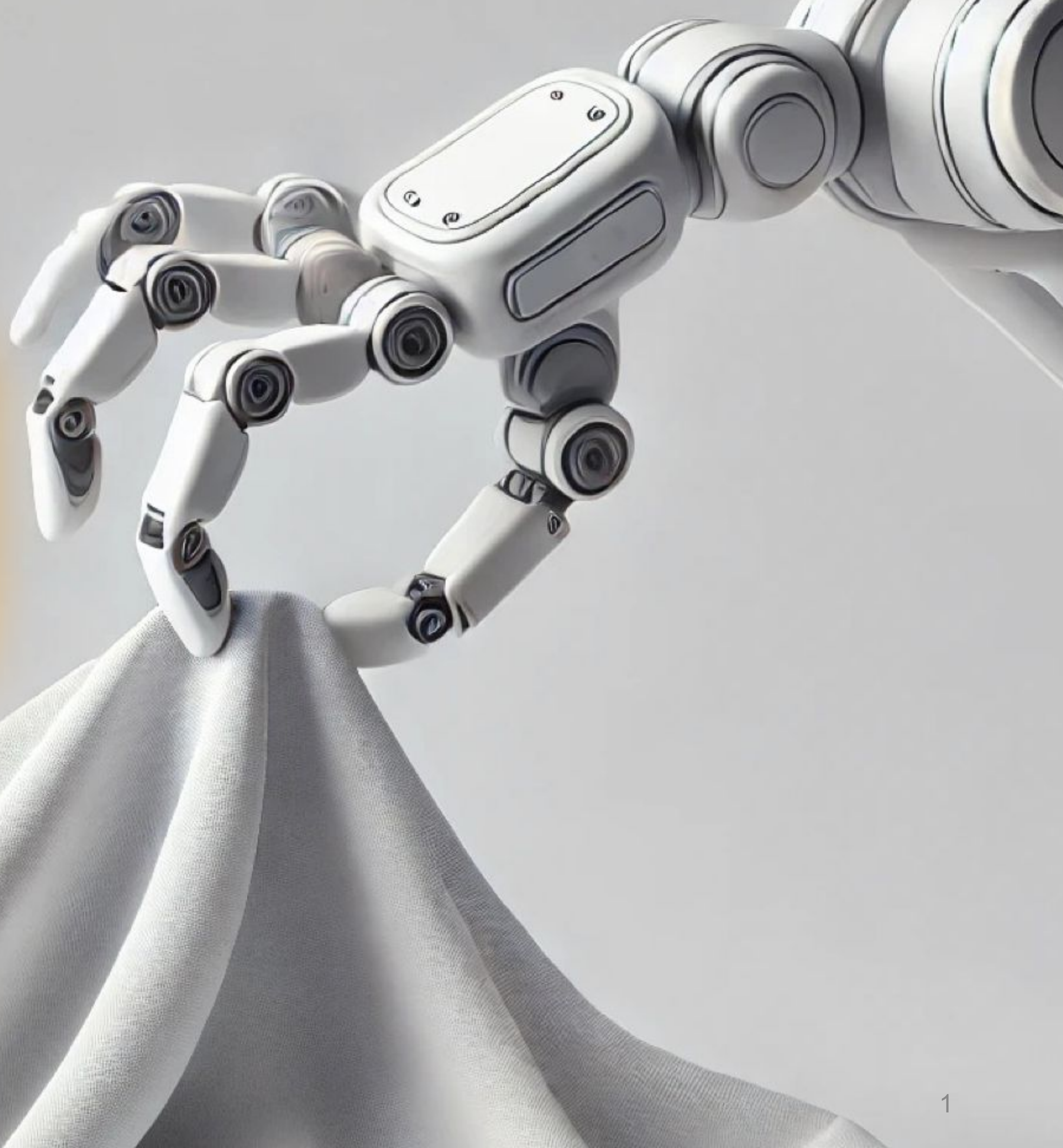
DeepRob

[Group 1] Lecture 04

Pranay, Aditya, Siddharth

Deformable Object Manipulation

University of Minnesota



Objects

Rigid Objects (Credits: YCB Objects and Models)

Objects

Rigid Objects (Credits: YCB Objects and Models)

Credits: PartNet-Mobility dataset

Credits: Dune 2021

Credits: GettyImages

Deformable Objects

- Linear
- Planar
- 3D objects

Linear Object

3D Object

Planar Objects

"Feature sensing and robotic grasping of objects with uncertain information: A review.", Wang, C., Zhang, X., Zang, X., Liu, Y., Ding, G., Yin, W., & Zhao, J. Sensors, 20(13), 3707 (2020).

Applications

Why do we even care about deformable objects?
- Healthcare
- Food Industry
- Textile
- Agriculture

Challenges

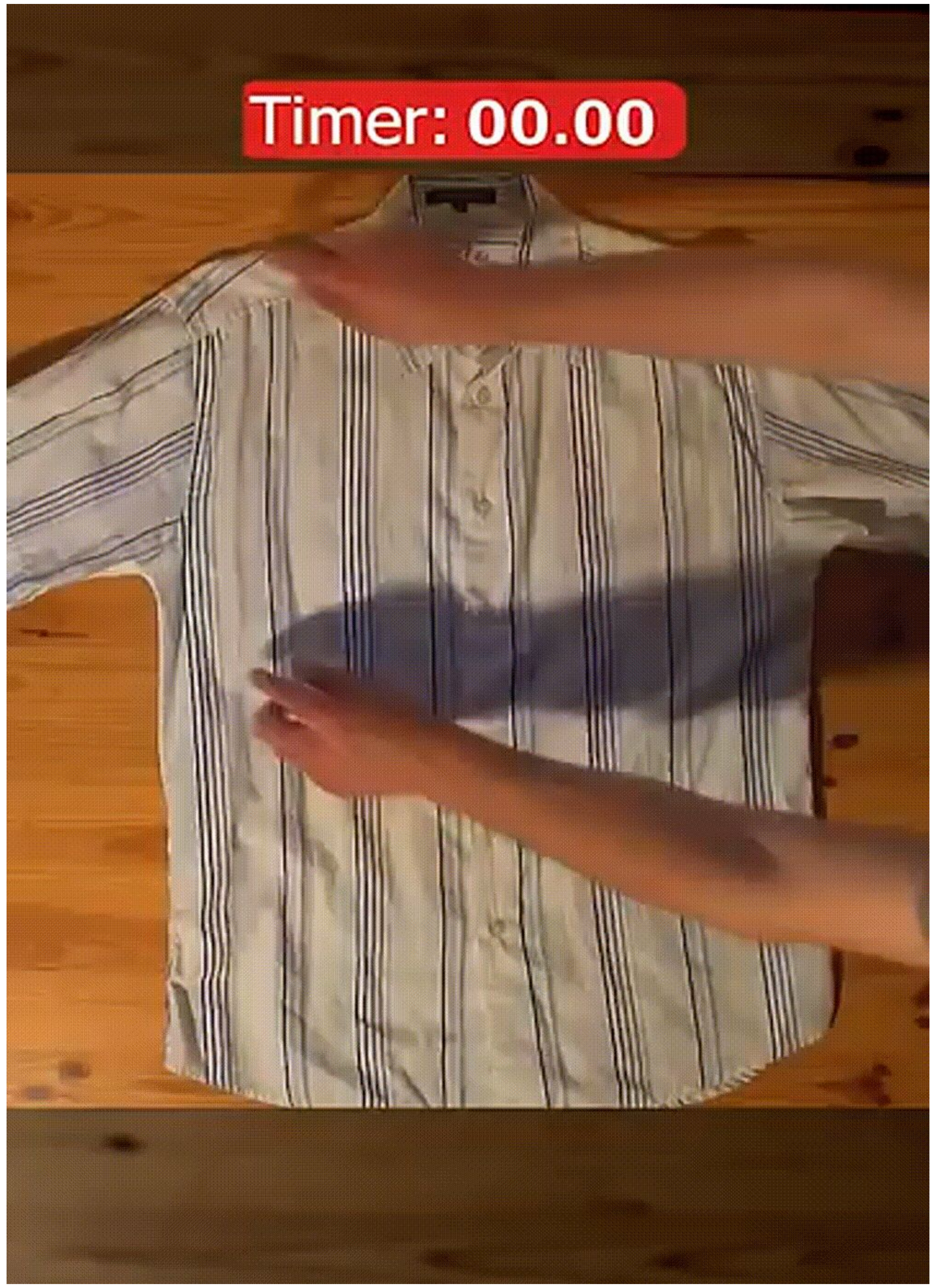
- Self Occlusion

- Complex dynamics

- High degrees of freedom

Credits: behance.net

Human vs Robot



Credits:@DaveHax

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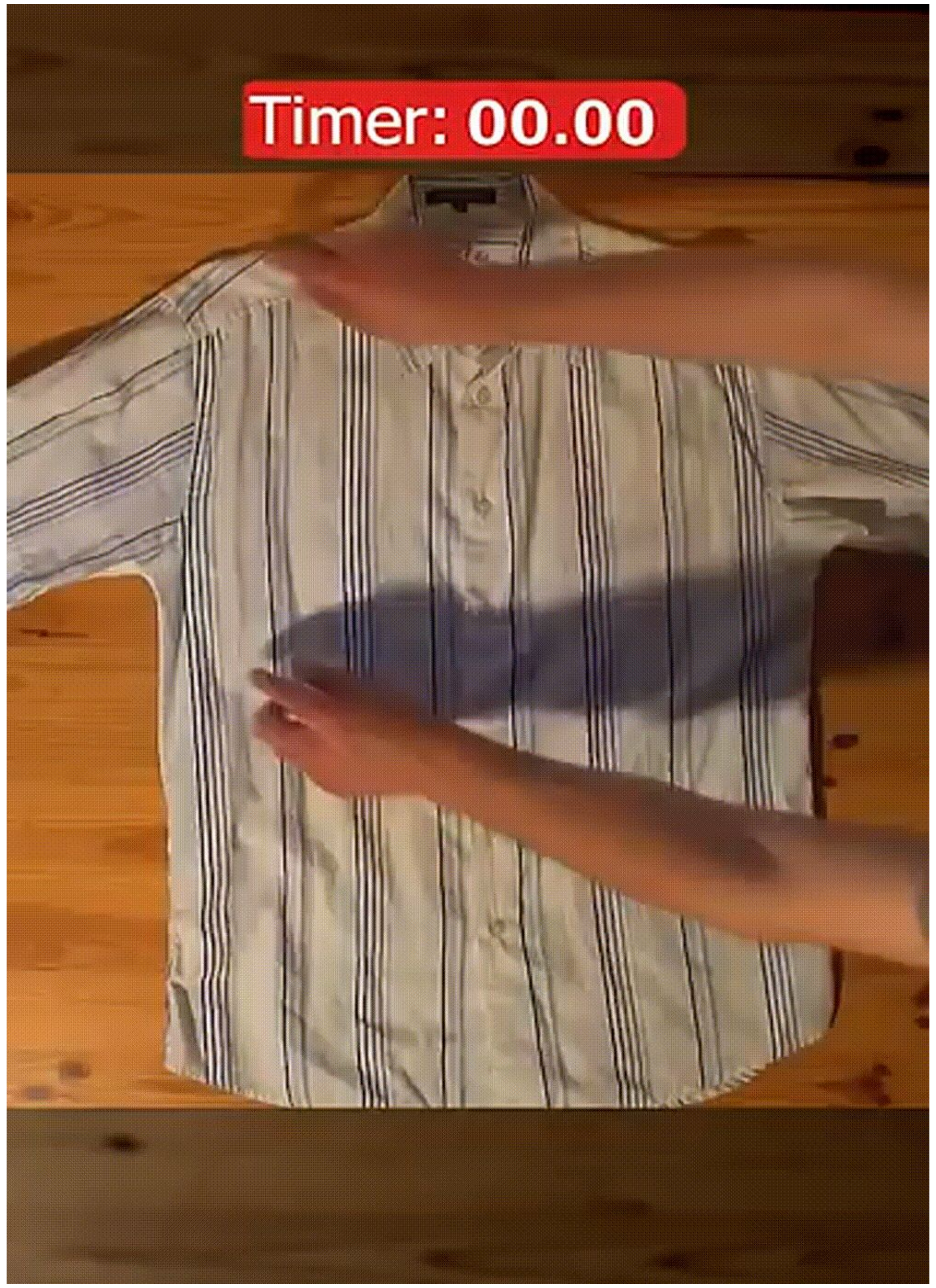


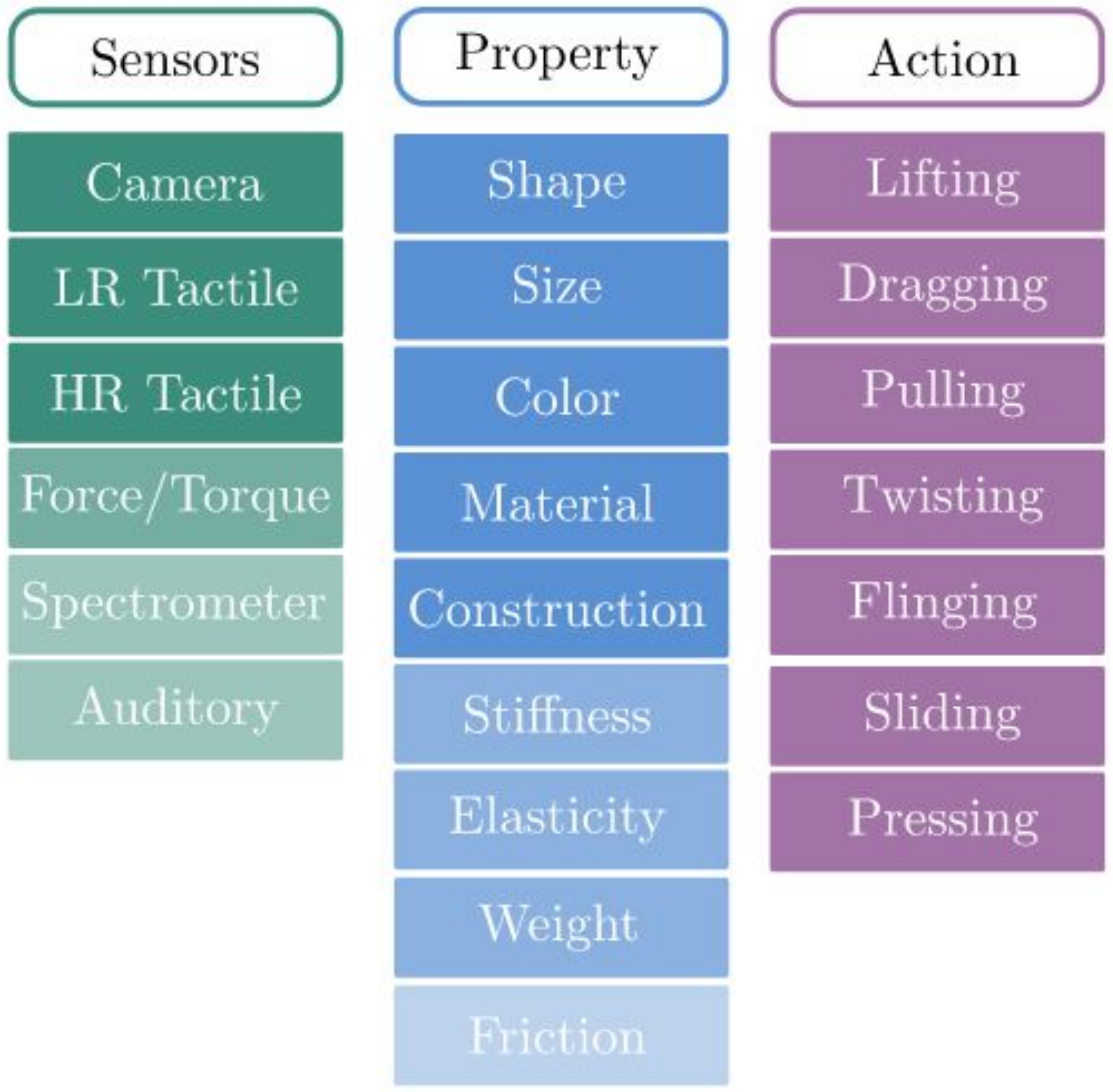
Credits:@DaveHax

Credits: pi0

Which Sensors? Sensing which properties? Actions?

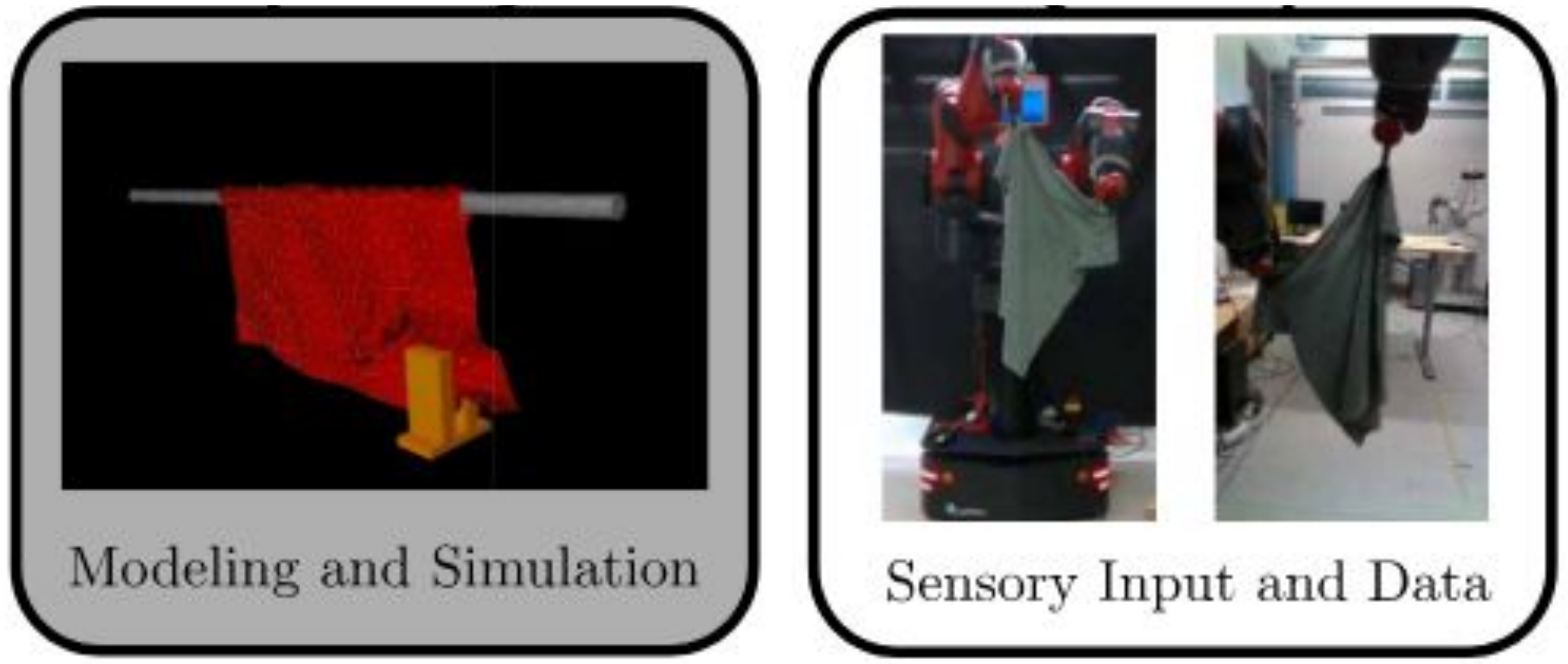
"pi0: A Vision-Language-Action Flow Model for General Robot Control", Black, K., Brown, N., Driess, D., Esmail, A., Equi, M., Finn, C., ... & Zhilinsky, U., arXiv preprint arXiv:2410.24164 (2024).

Decoding Deformable Object Manipulation



"Unfolding the literature: A review of robotic cloth manipulation.", Longhini, Alberta, Yufei Wang, Irene Garcia-Camacho, David Blanco-Mulero, Marco Moletta, Michael Welle, Guillem Alenyà et al. arXiv preprint arXiv:2407.01361 (2024).

End-to-end Workflow



"Modeling, learning, perception, and control methods for deformable object manipulation.", Yin, Hang, Anastasia Varava, and Danica Kragic, Science Robotics 6.54 (2021)

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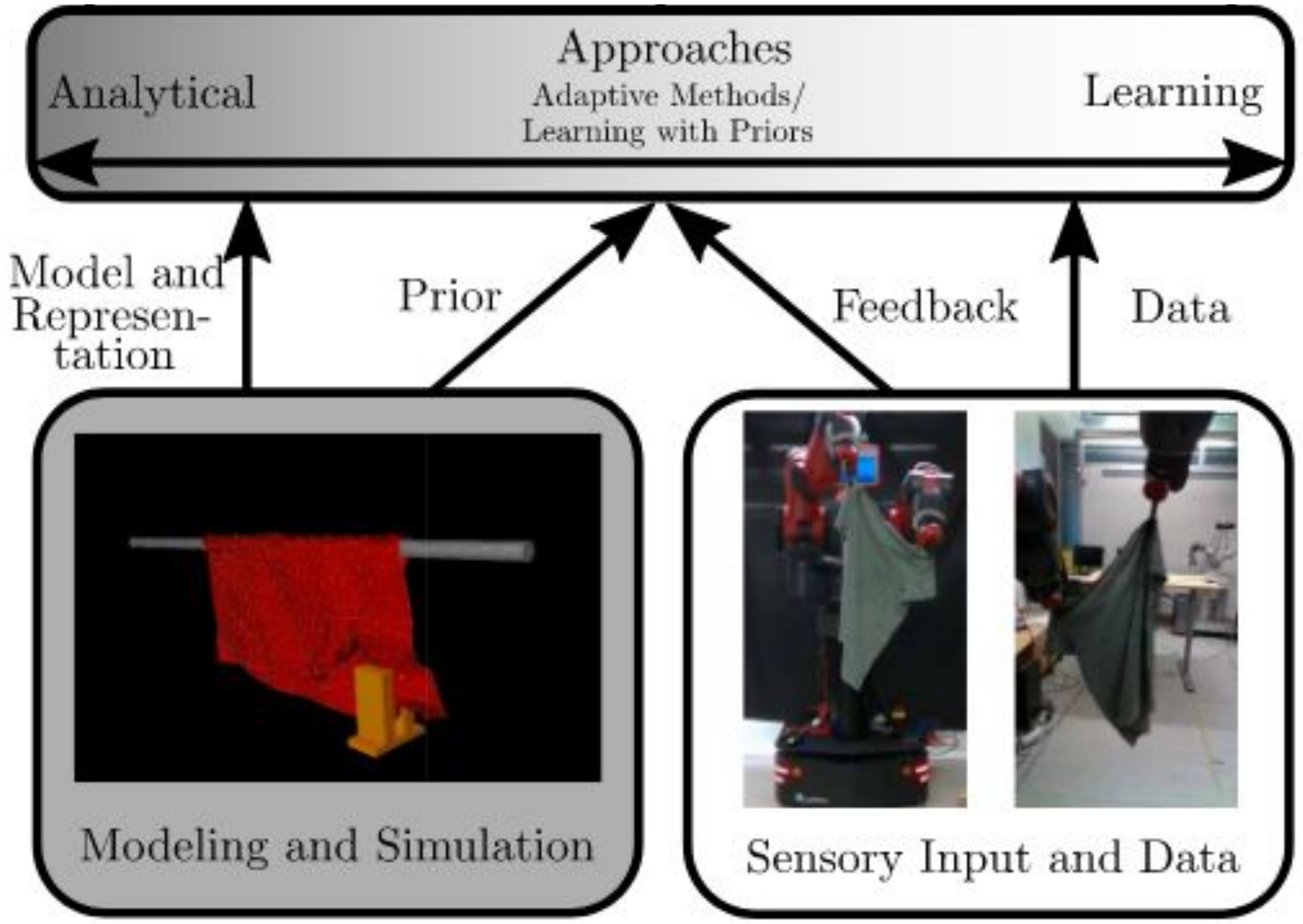

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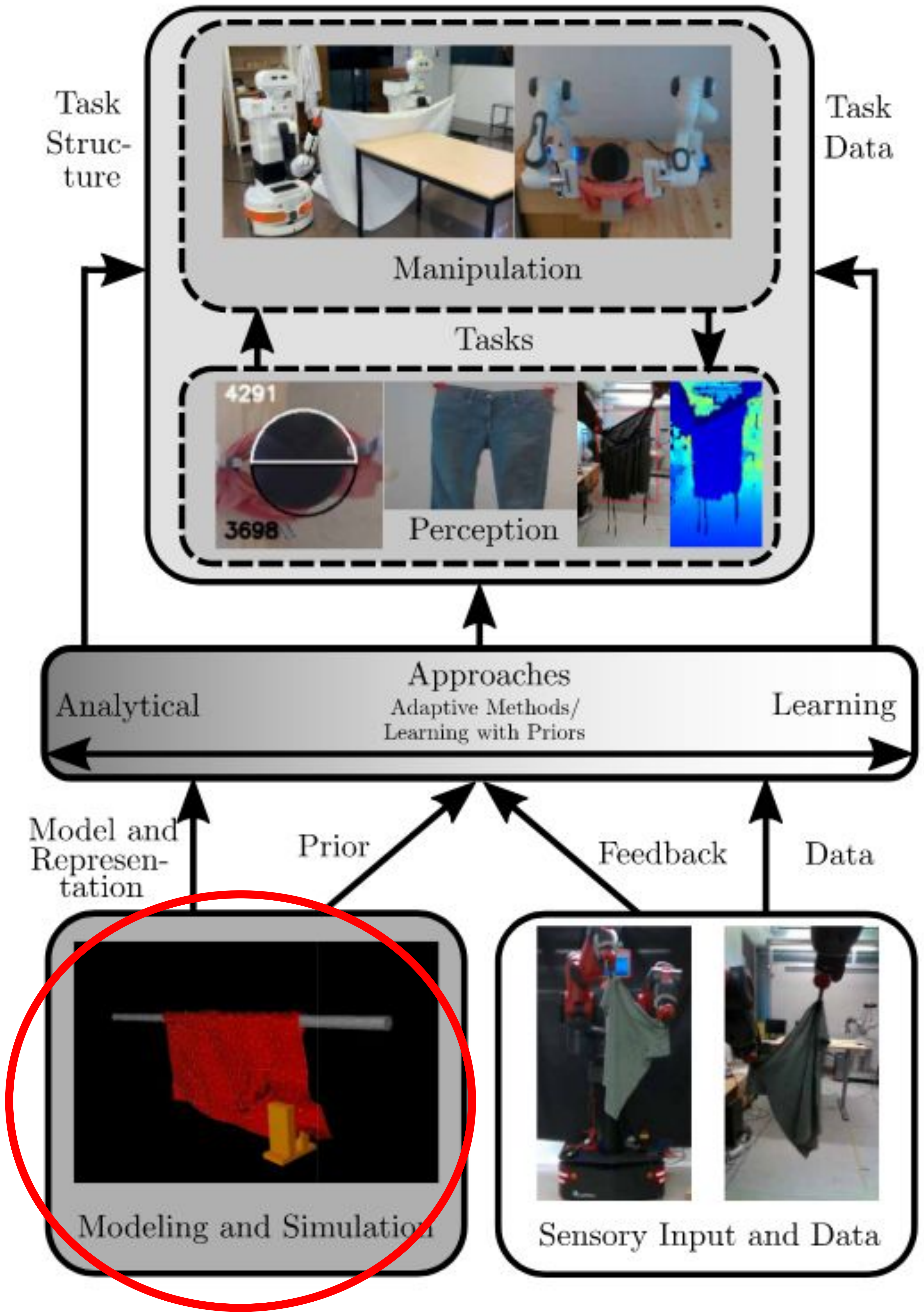
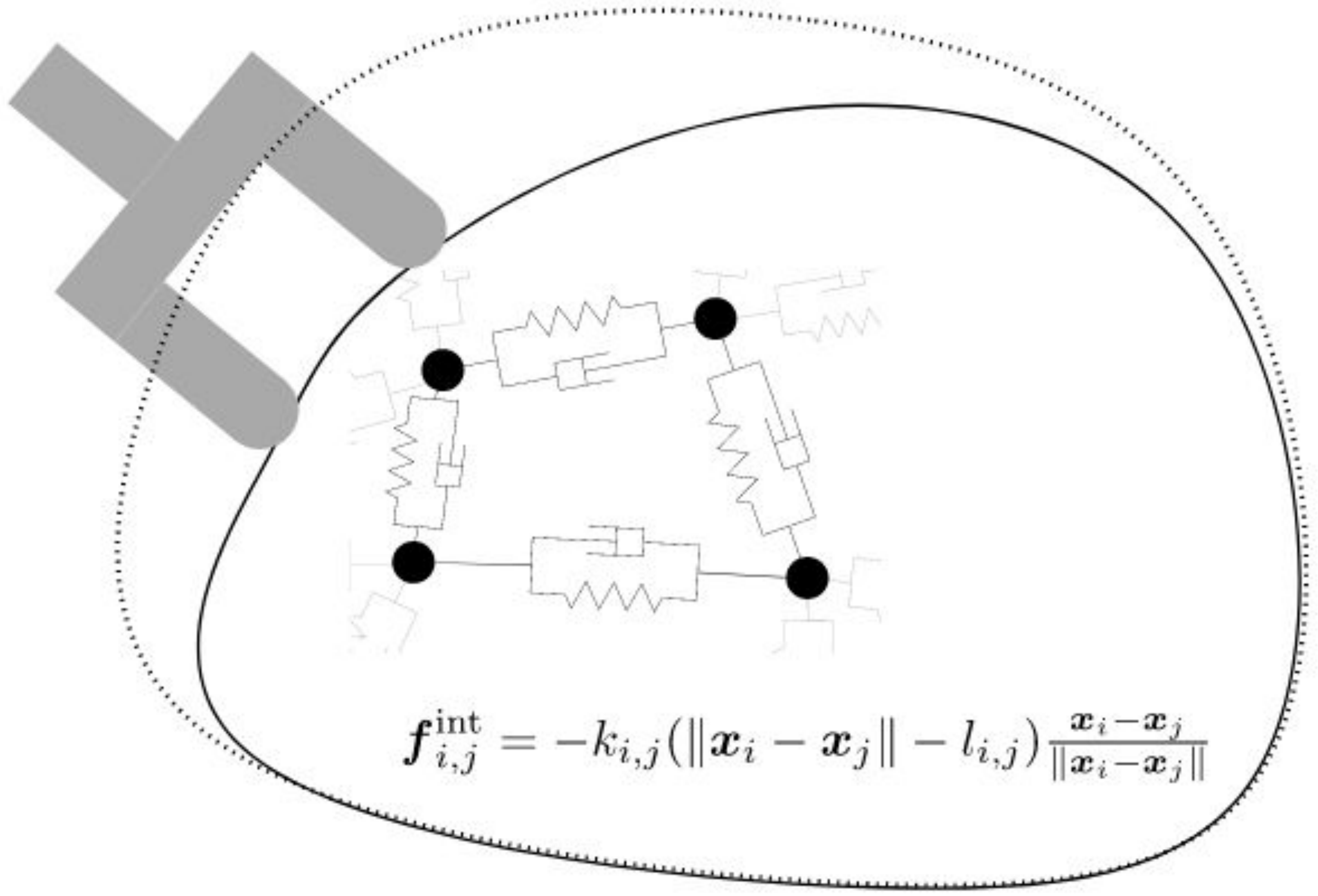


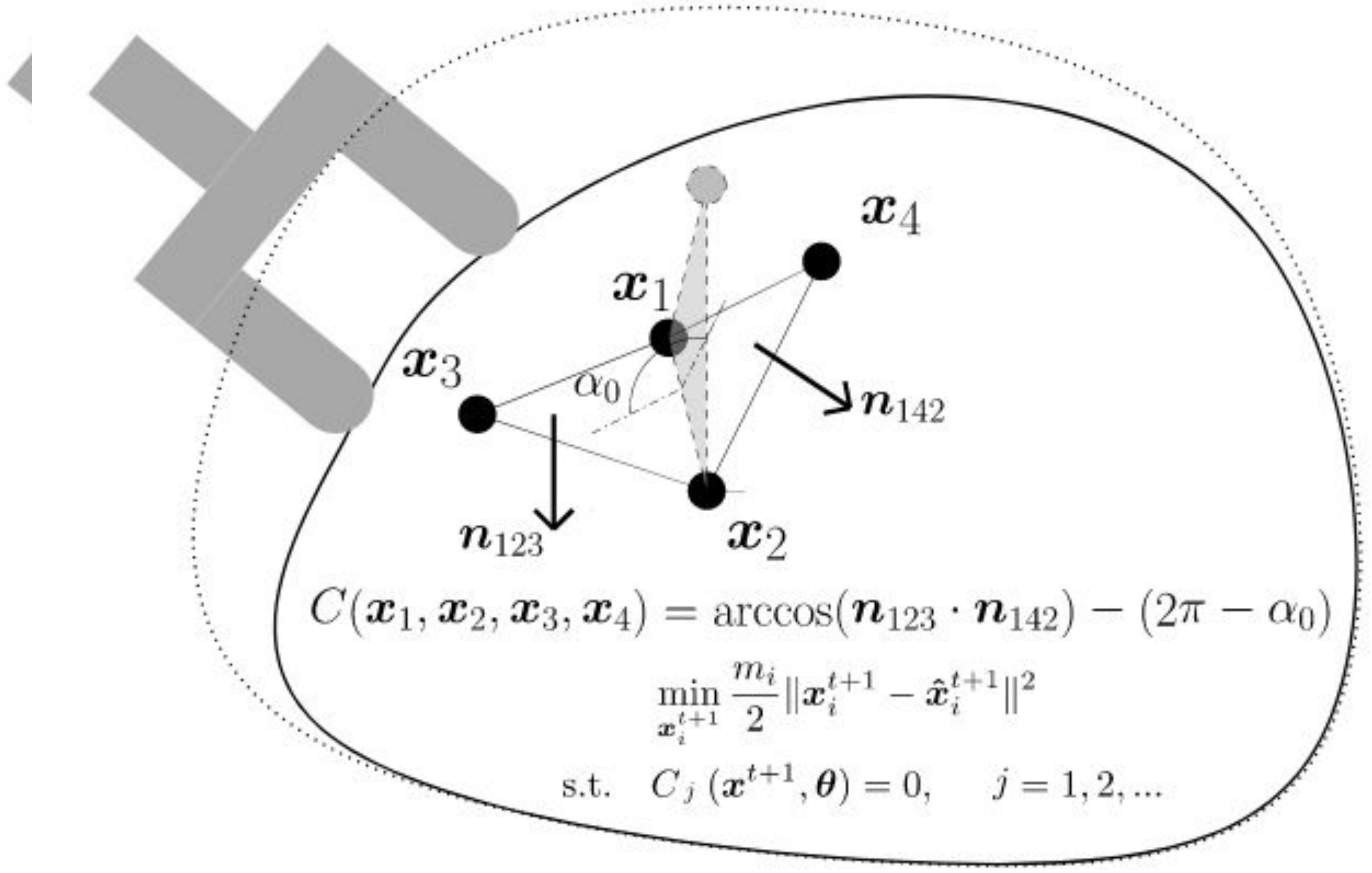
"Modeling, learning, perception, and control methods for deformable object manipulation.", Yin, Hang, Anastasia Varava, and Danica Kragic, Science Robotics 6.54 (2021)

Physics-based Modeling of deformable objects

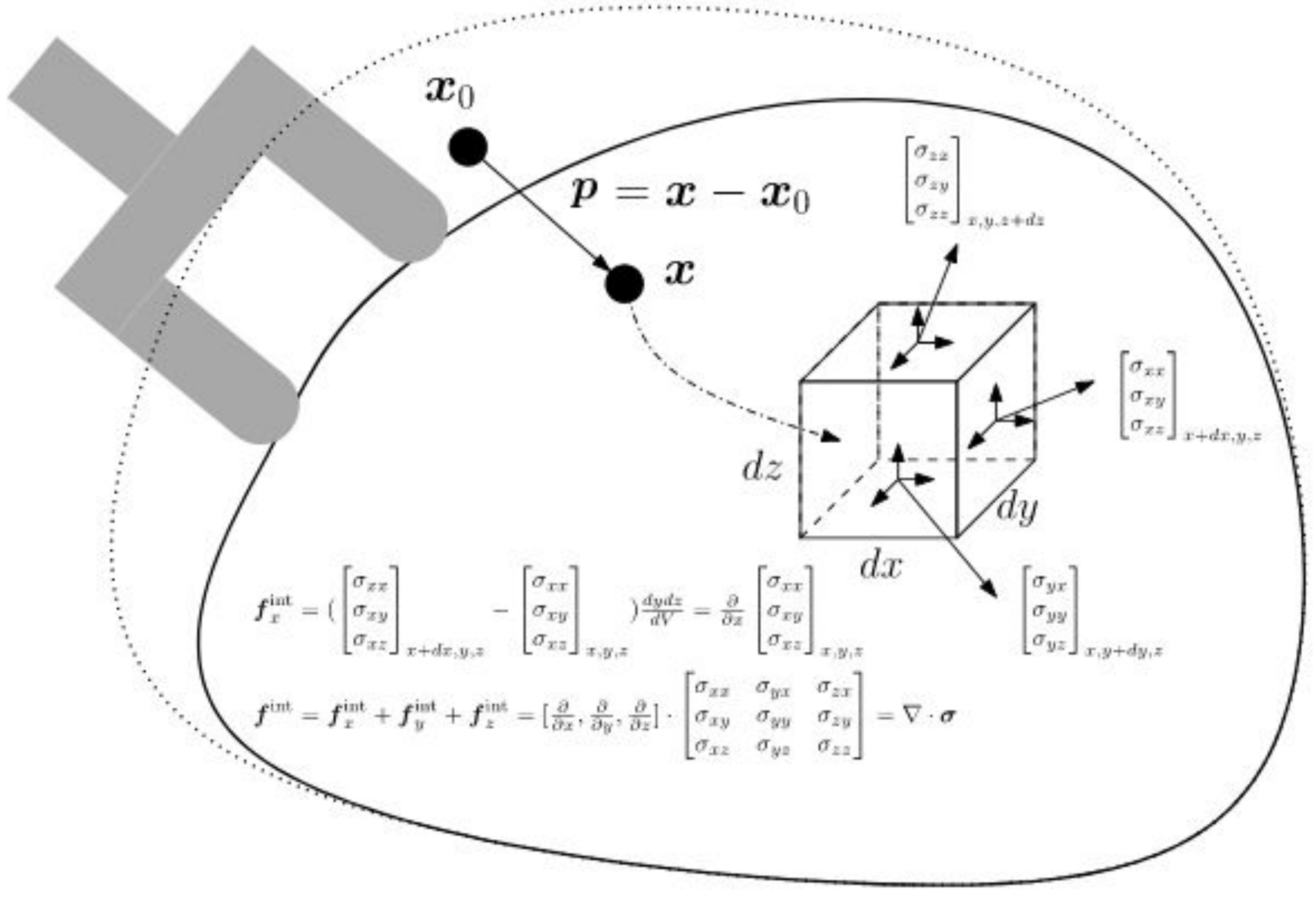
a) Mass-spring systems



b) Position-based dynamics



c) Continuum mechanics



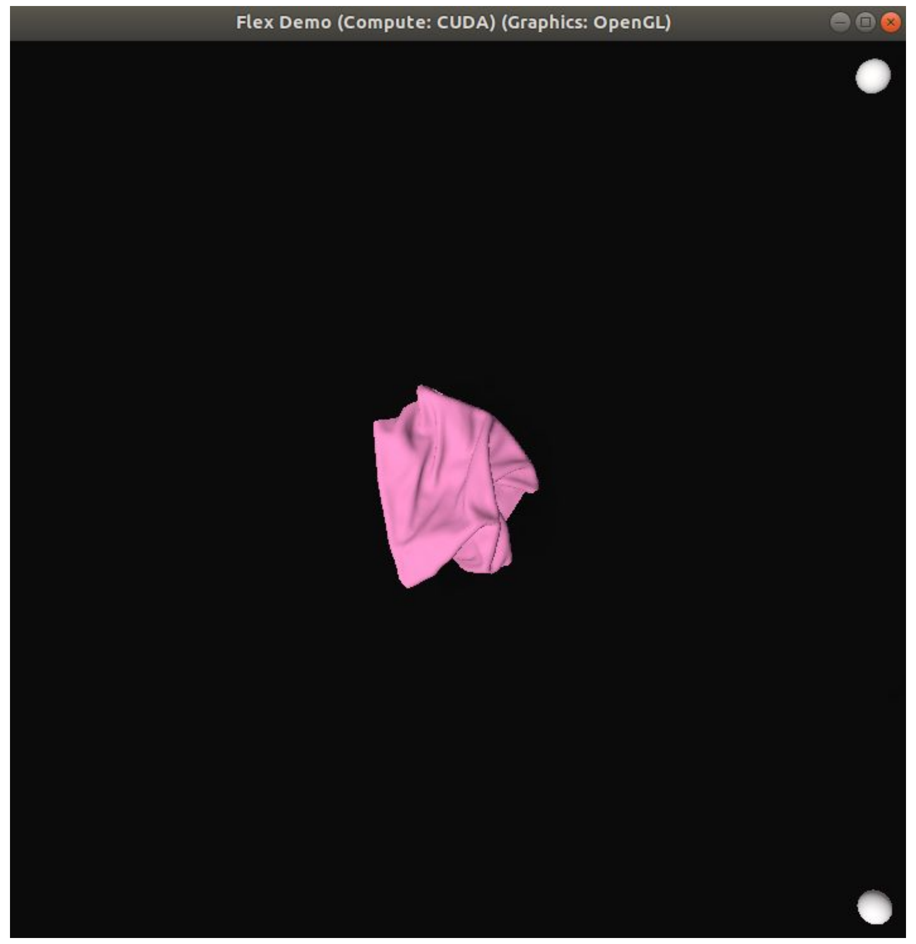
Simulators

- Softgym

- MuJoCo

- SOFA

- PyBullet



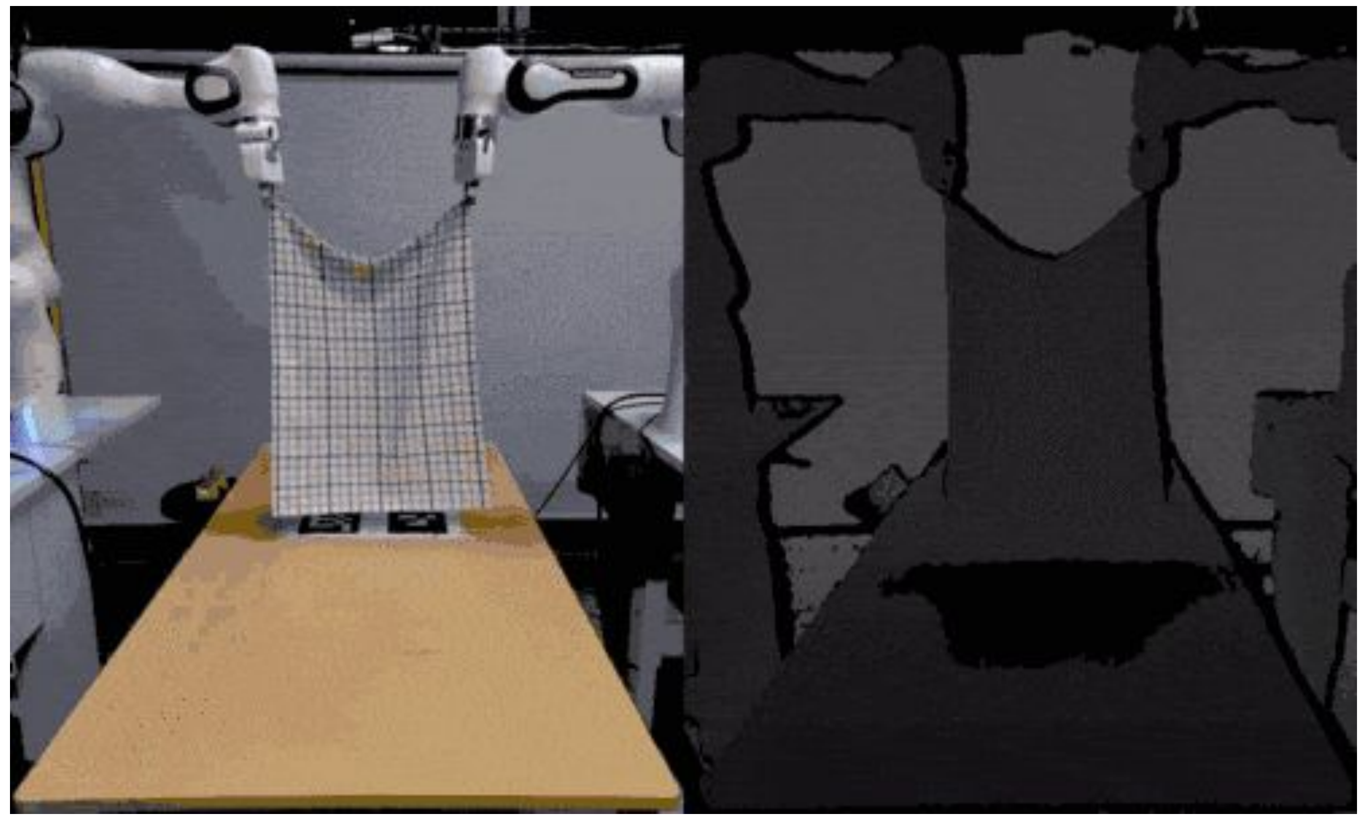
Softgym built on Nvidia FleX bindings

SOFA Simulation Open Framework Architecture

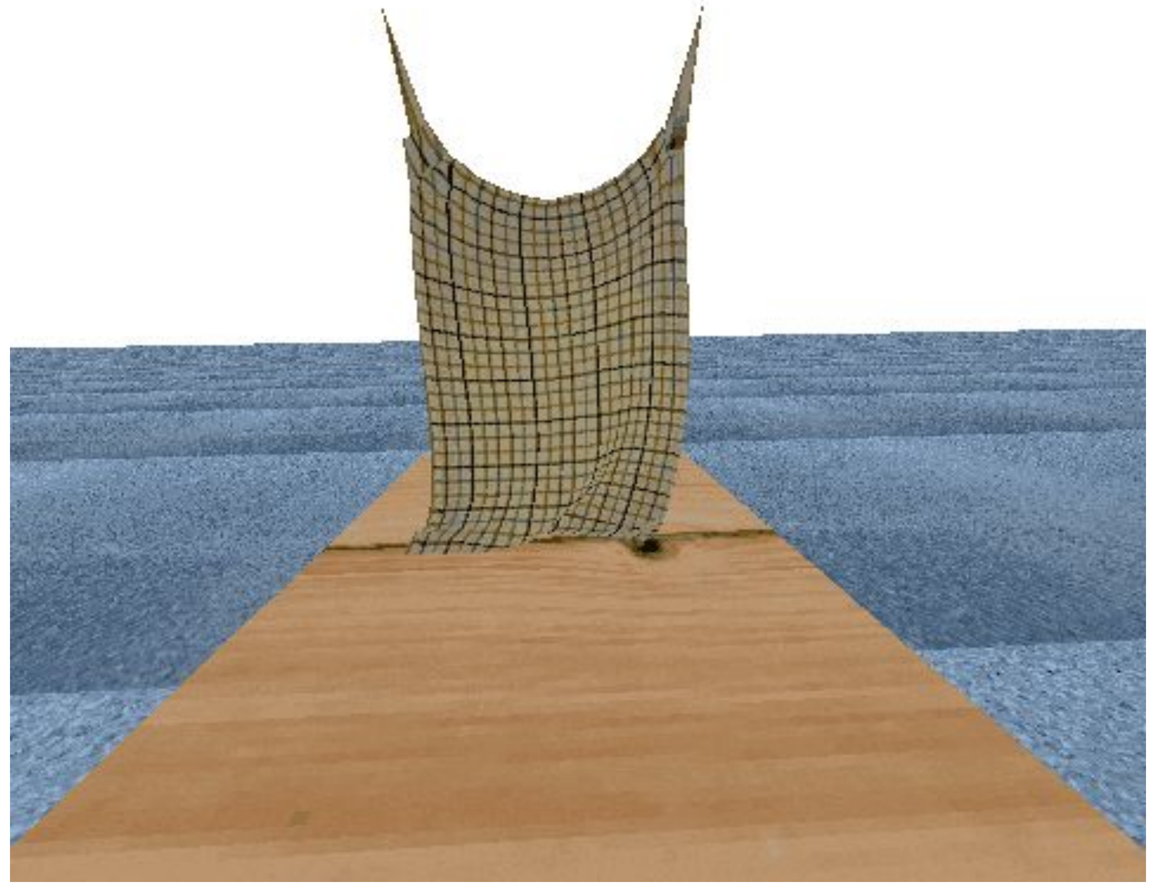
MuJoCo
Advanced physics simulation

"Softgym: Benchmarking deep reinforcement learning for deformable object manipulation," X. Lin, Y. Wang, J. Olkin, and D. Held, in Conference on Robot Learning (CoRL), 2021.

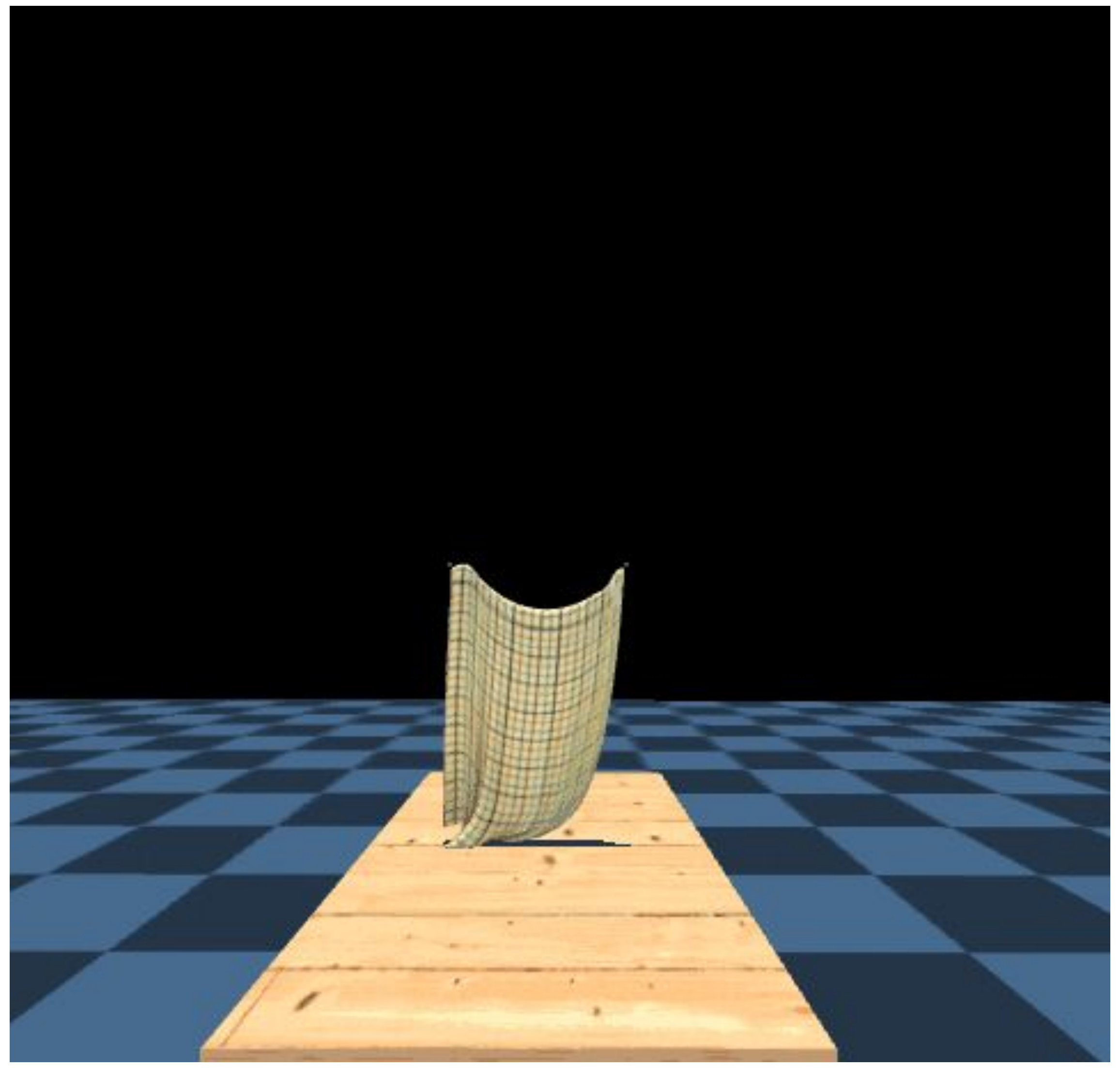
Simulators



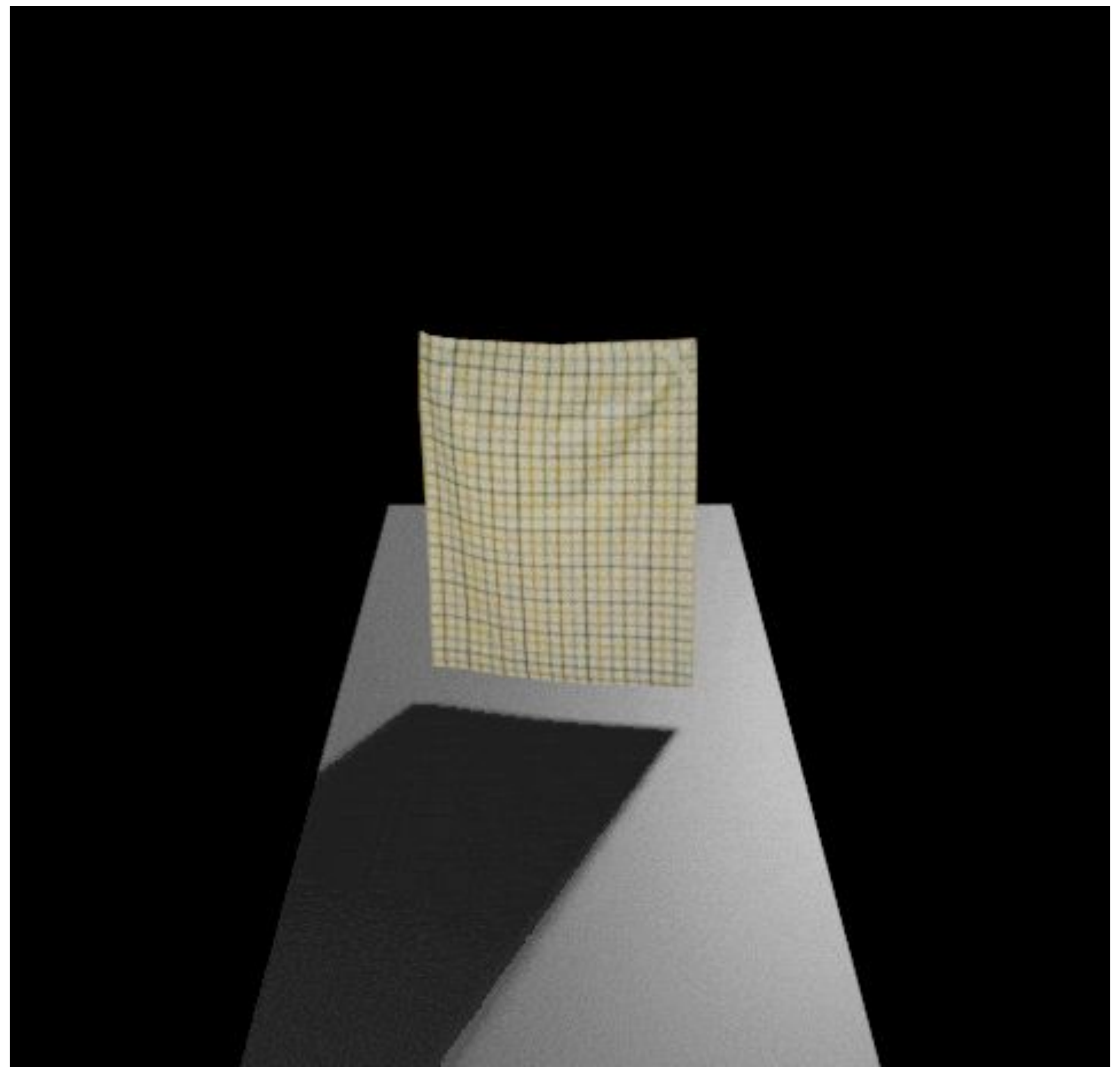
Real-world Demonstration



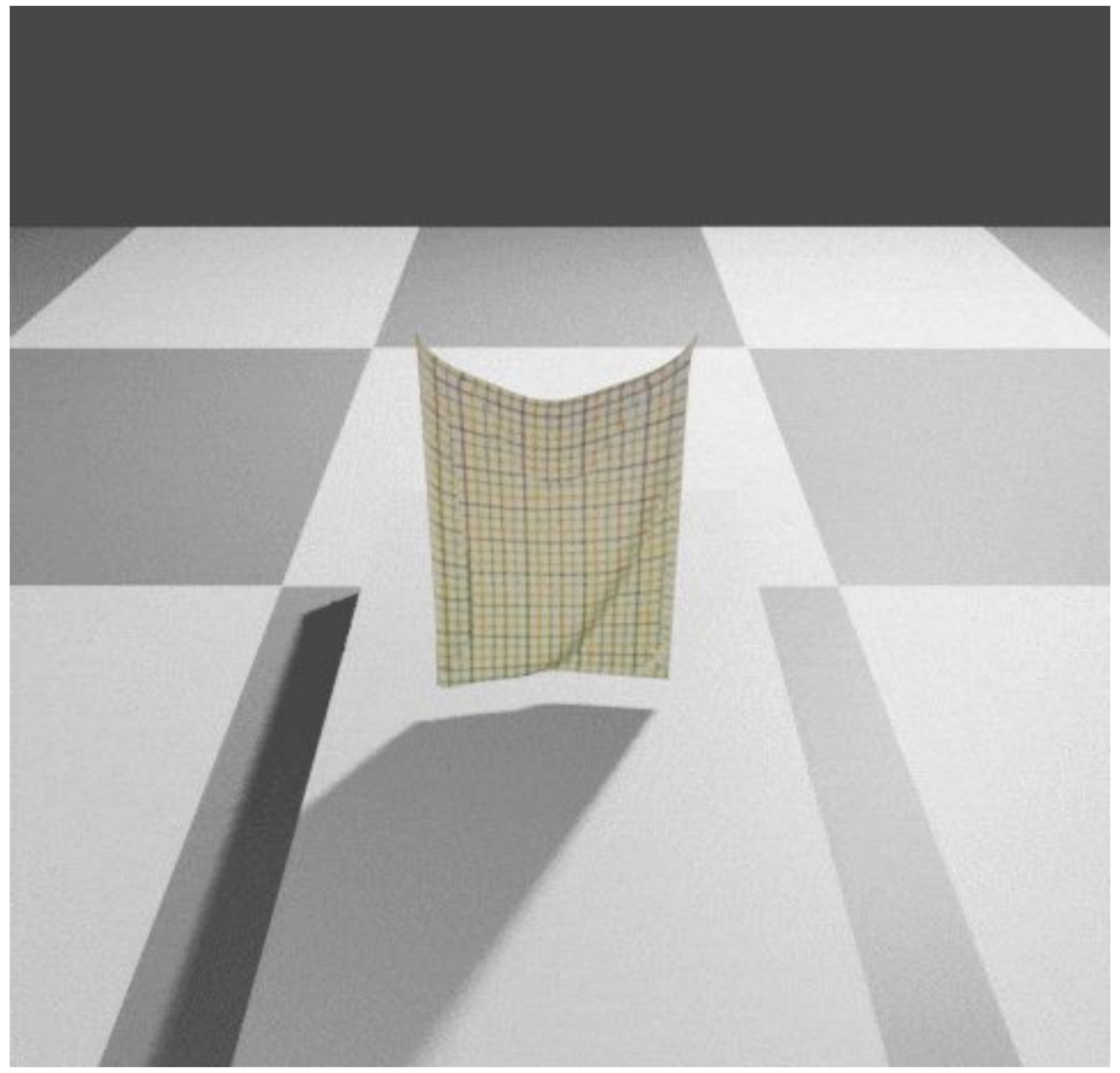
Bullet



MuJoCo



SOFA



Softgym

Credits: “Benchmarking the sim-to-real gap in cloth manipulation”, Blanco-Mulero, D., Barbany, O., Alcan, G., Colomé, A., Torras, C., & Kyrki, V. IEEE Robotics and Automation Letters.(2024).

Traditional Methods: Before Deep Learning

- Contour Matching

- Template Matching

- Simple ML models

Lets understand this with an example work!

Ref

“Perception for the Manipulation of Socks”, Ping Chuan Wang, Stephen Miller, Mario Fritz, Trevor Darrell, Pieter Abbeel, 2011

- Input:
  - Single Image
- Output:
  - Structure(toe, ankle, etc)
  - Inside-out?
  - Match with candidates
- Use of LBP, MR8 filter banks
- Use of SVM classifier

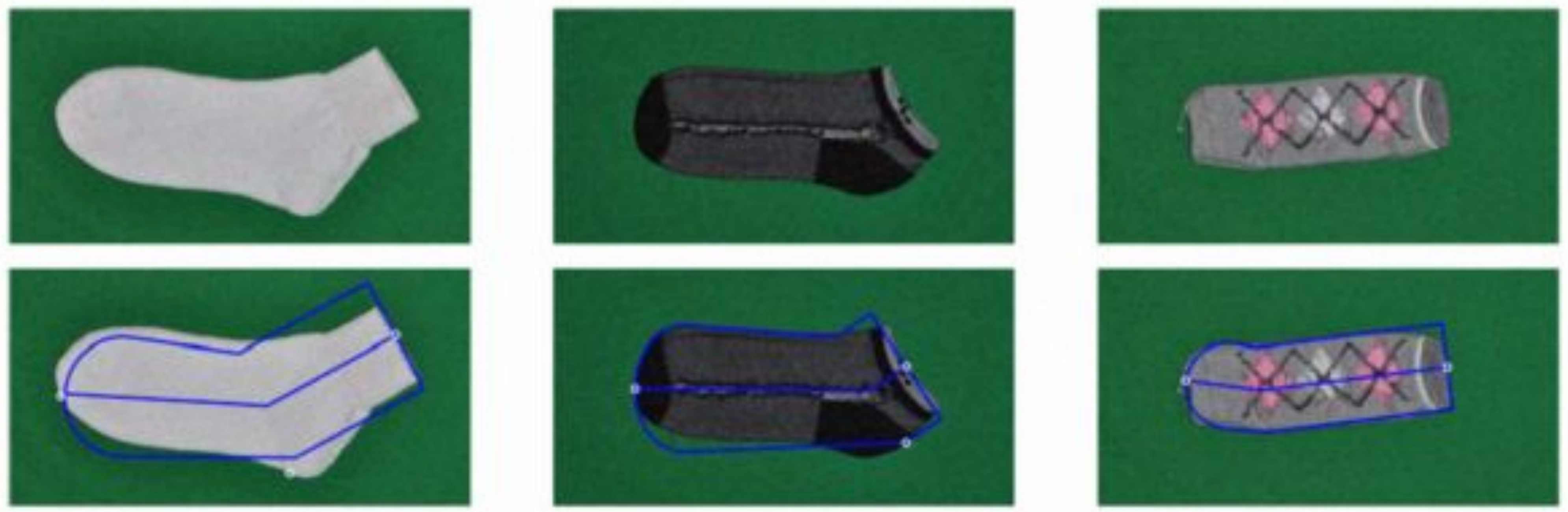


Fig. 1. Given an initial image, we wish to recover the sock configuration.

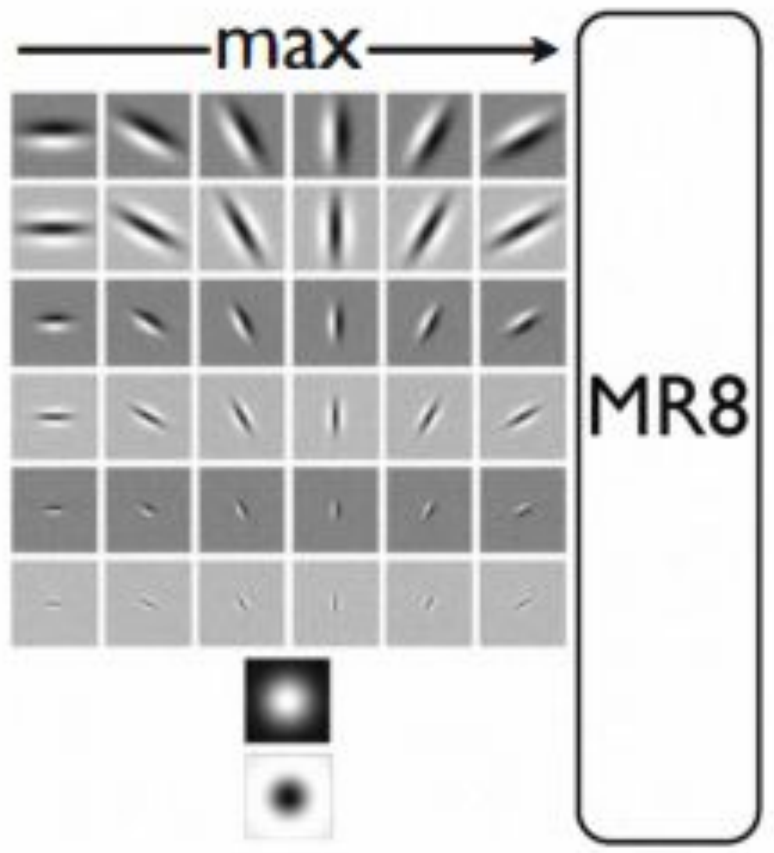


Fig. 3. The MR8 filter bank consists of 6 gaussian derivative and 2 blob filters. A maximum operations is performed over different orientation variants in order to achieve robustness with respect to rotations.

“Perception for the Manipulation of Socks”, Ping Chuan Wang, Stephen Miller, Mario Fritz, Trevor Darrell, Pieter Abbeel, 2011

Project web page at: http://rll.berkeley.edu/2011 IROS socks

After Deep Learning

Data-Driven Models

- Advantages over Physics-based techniques:
    - Greater flexibility in defining state space

Data-Driven Models

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Solution?

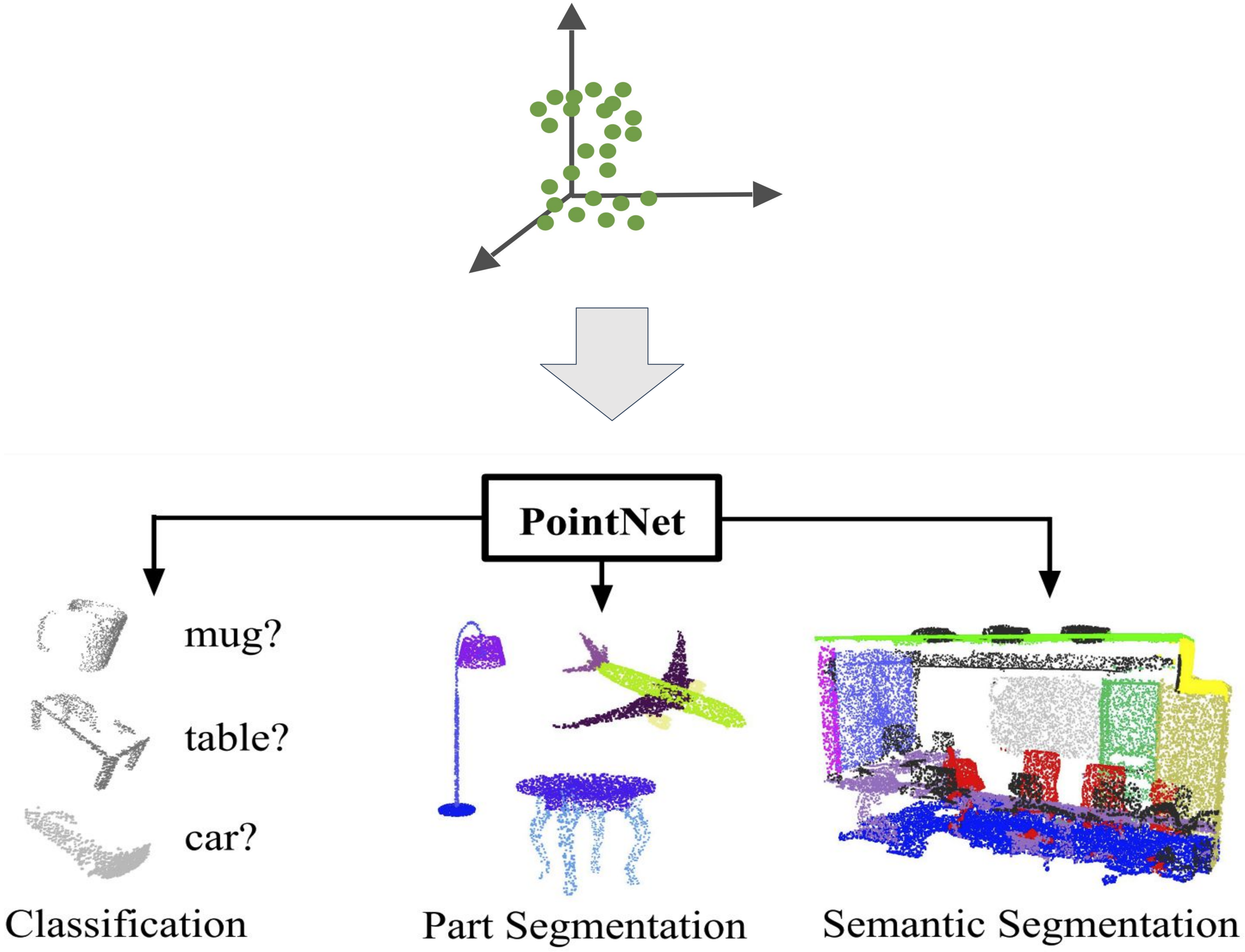
Particle-based Representations

- Rely on 3D Geometric representations (Particles/Meshes) ⟶ Robust to changes in Visual conditions.
- Such representations require specific architectures ⟶ Capture local structures & Handle data sparsity efficiently.
- PointNet++ for unordered point sets & Graph Neural Networks (GNNs) for mesh-based representations.

Point Cloud based
Representation of cloth

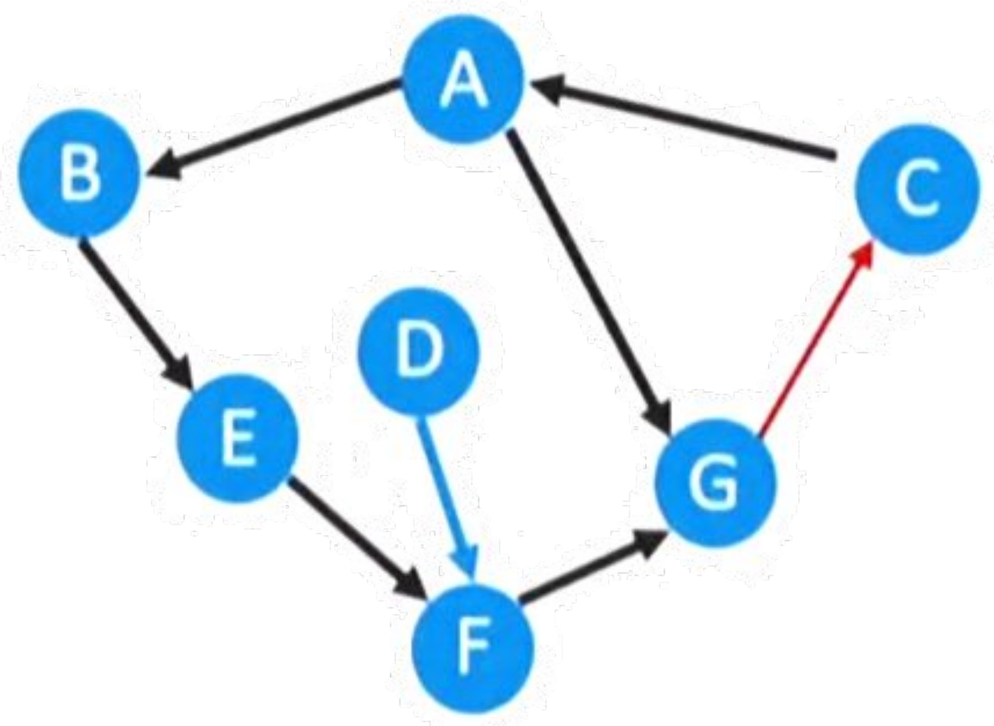
Mesh-grid based
Representation of cloth

PointNet

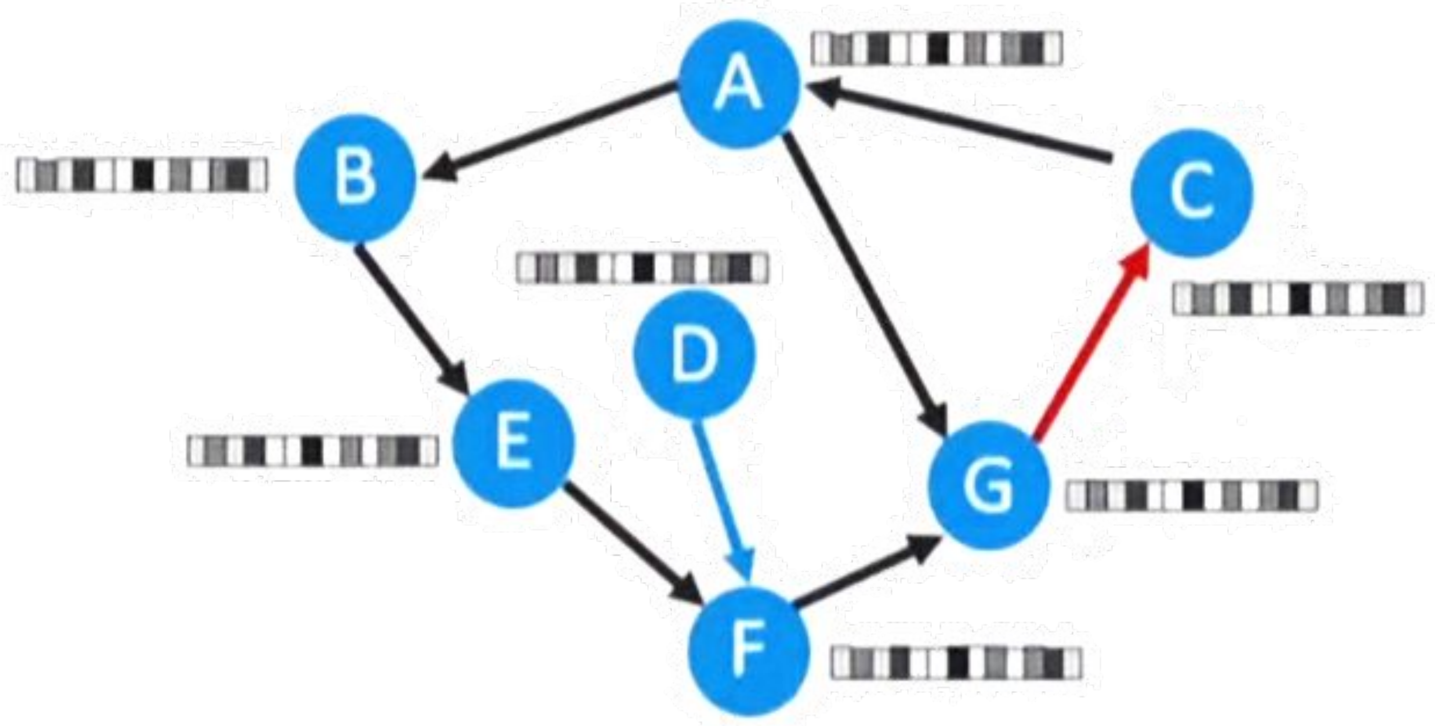


Qi, Charles R., et al. "Pointnet: Deep learning on point sets for 3d classification and segmentation." Proceedings of the IEEE conference on computer vision and pattern recognition. 2017.

Graph Neural Networks

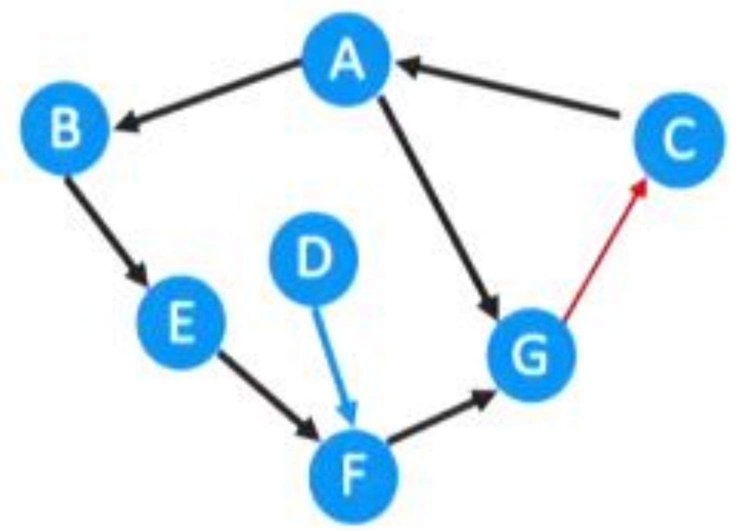


Graph Representation
of Problem



Initial Representation
of each node

Graph Neural Networks



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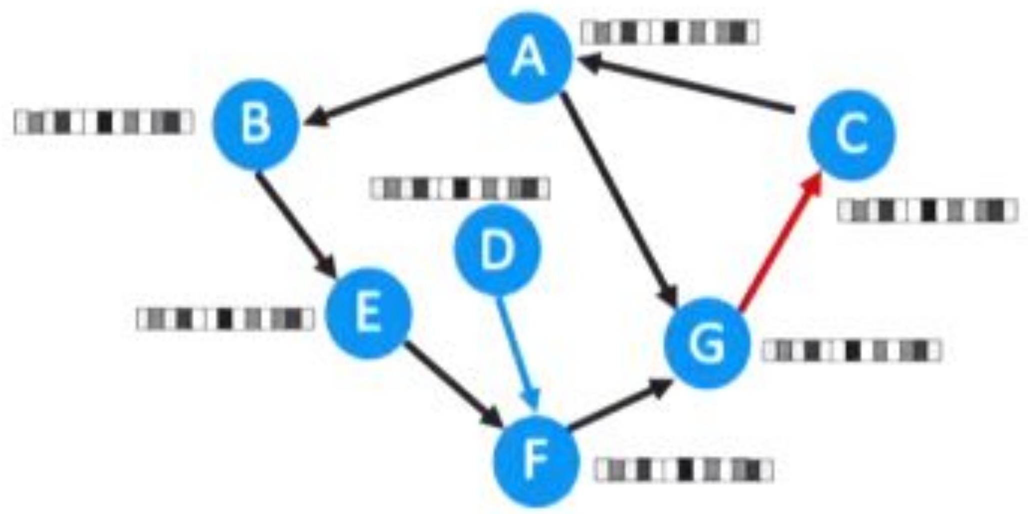

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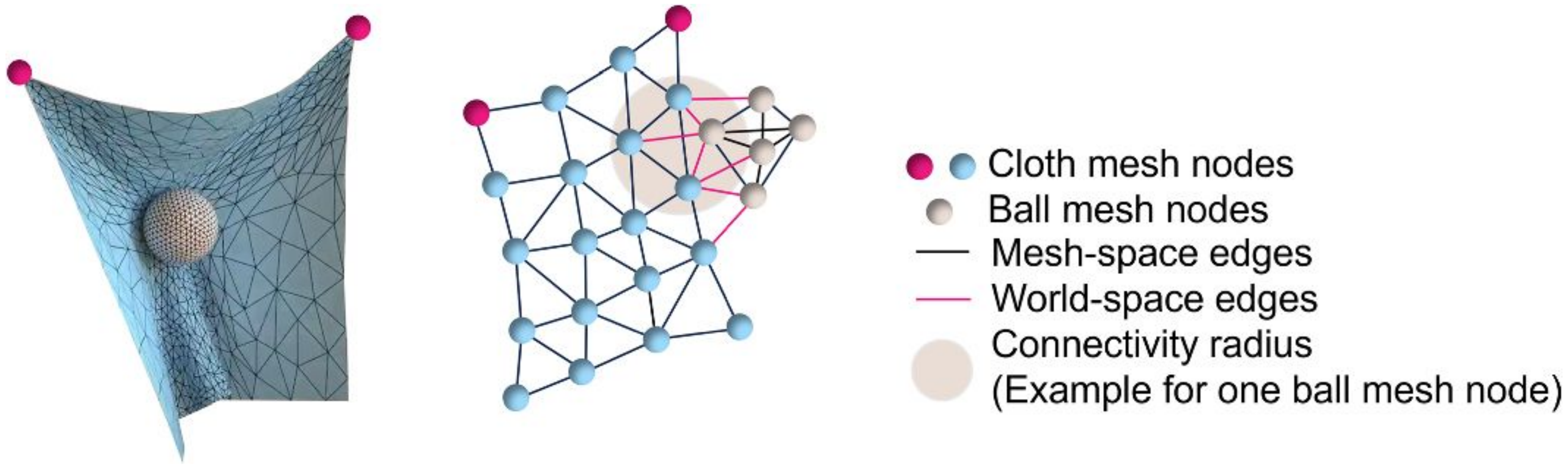

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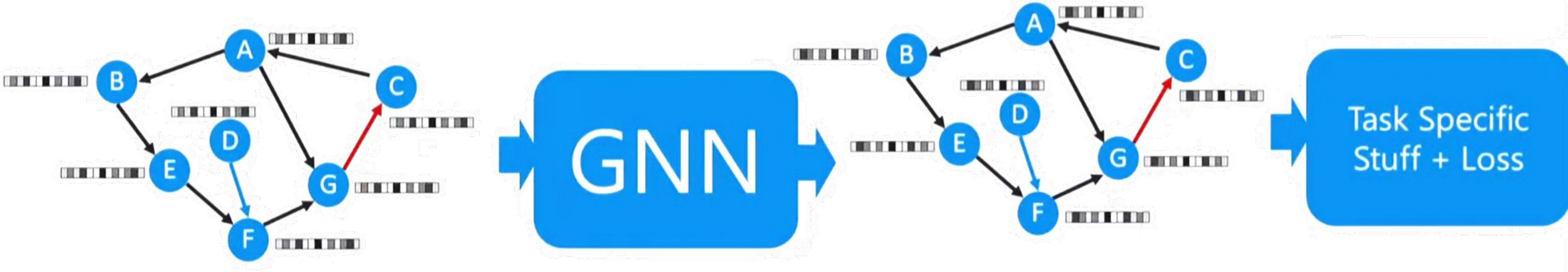
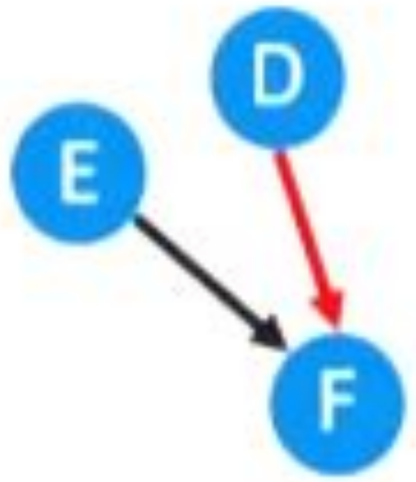


Initial Representation
of each node

Output Representations
of each Node

Neural Message Passing



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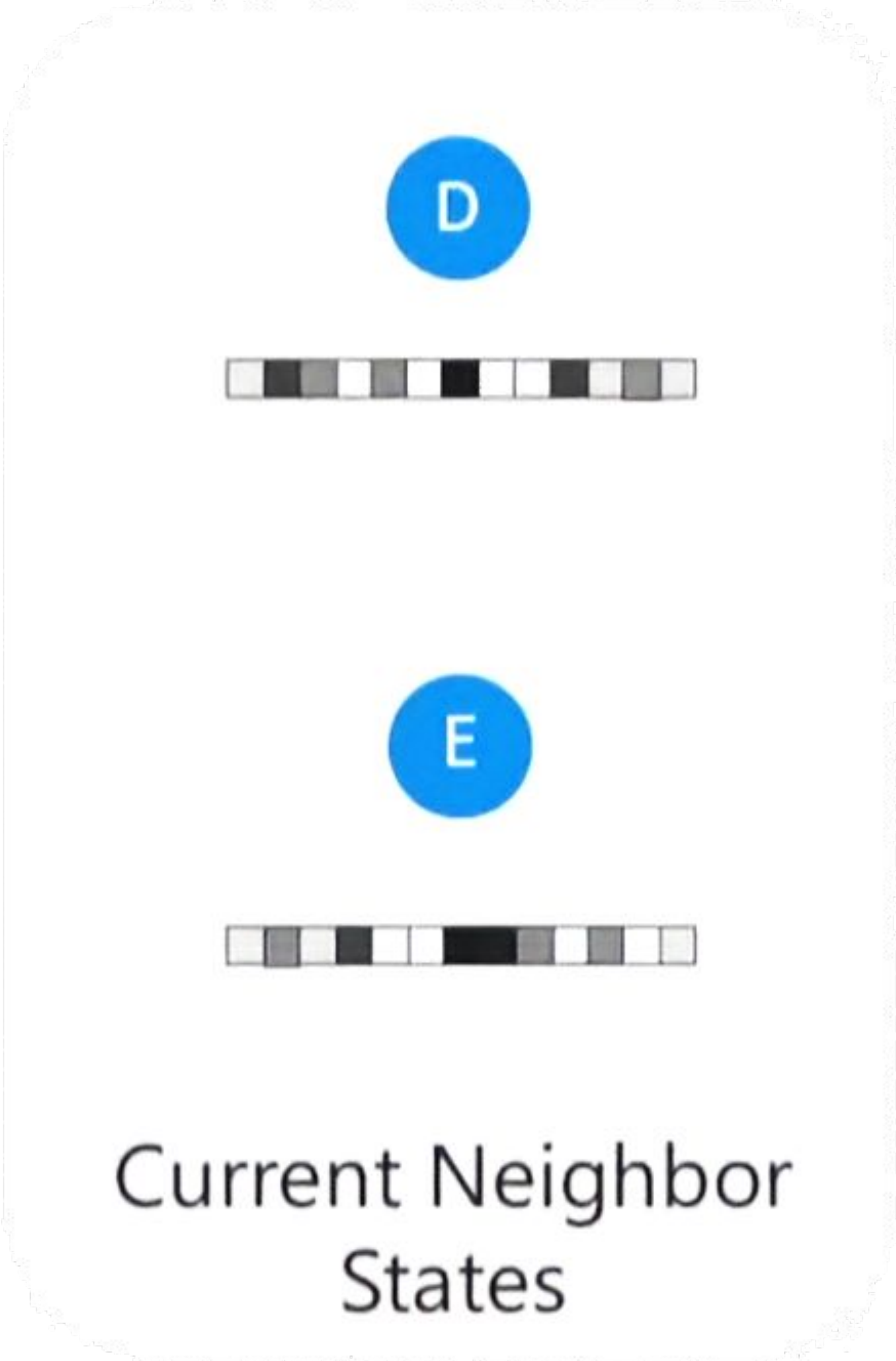
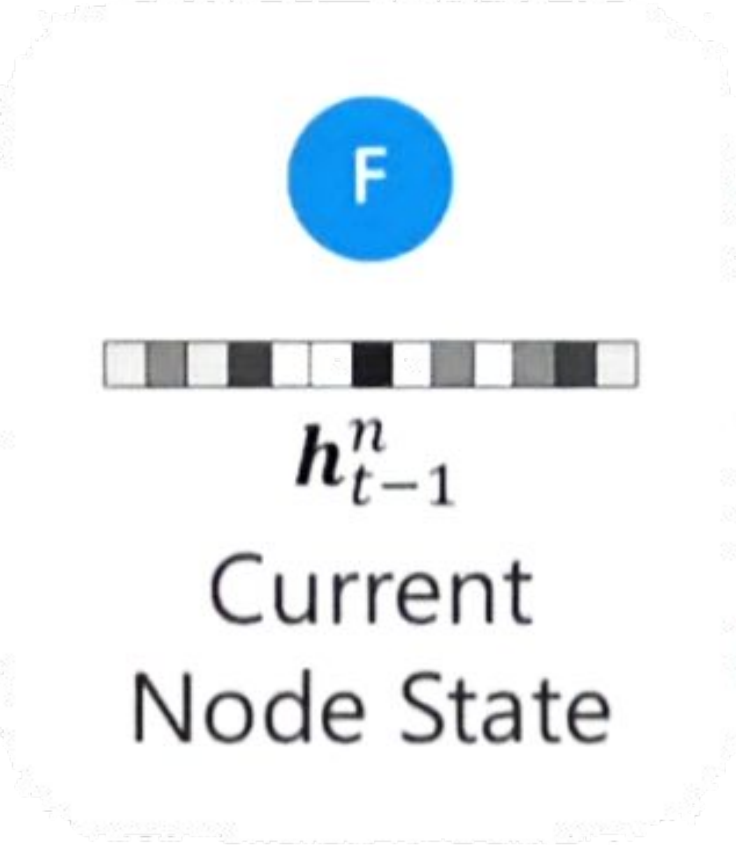
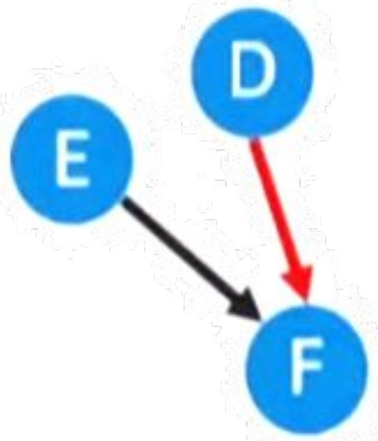
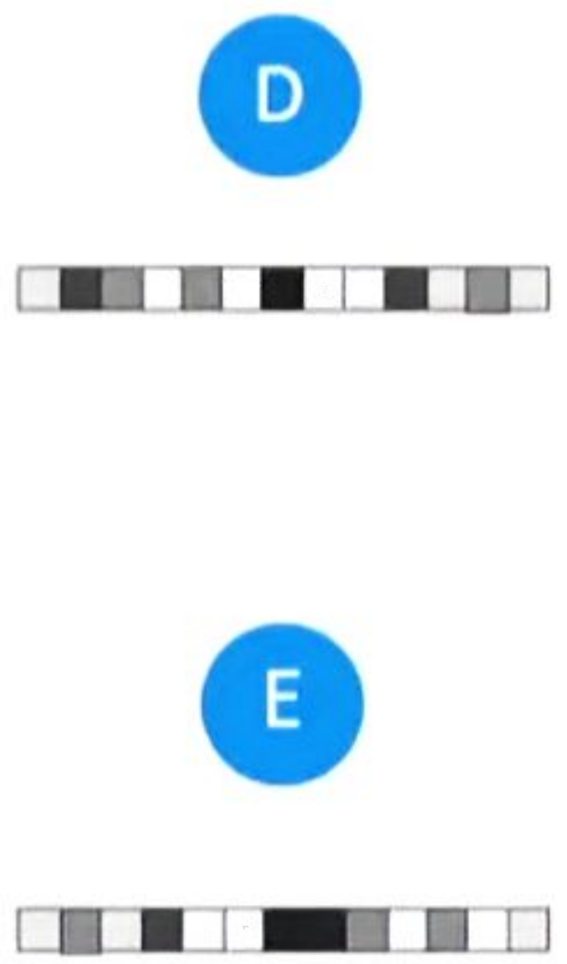




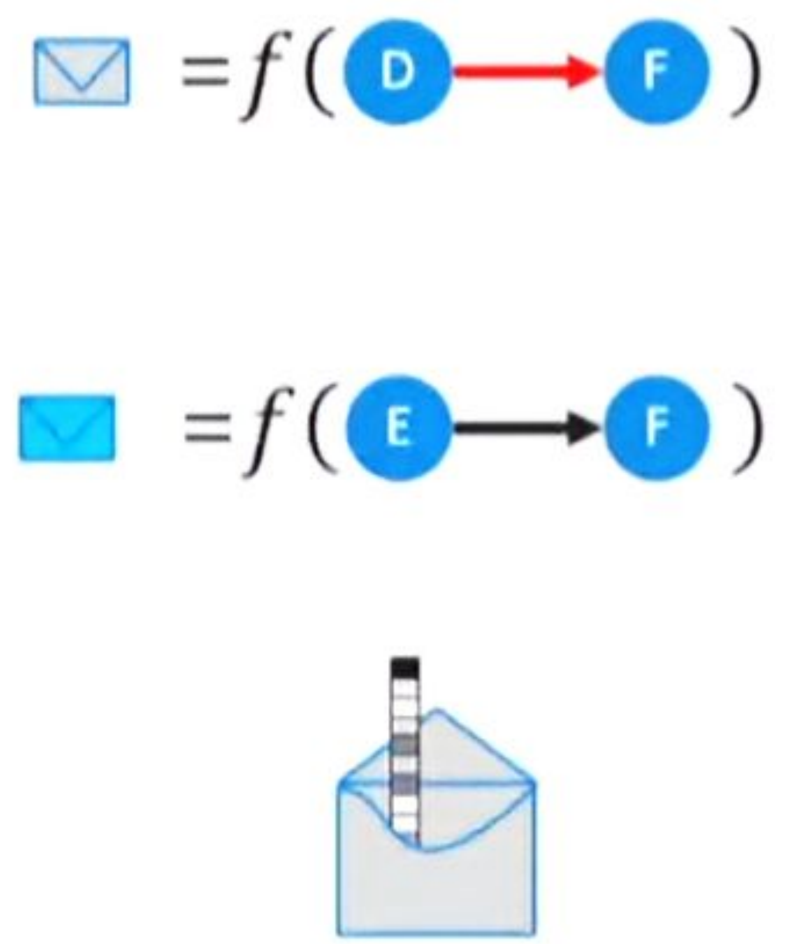


Neural Message Passing

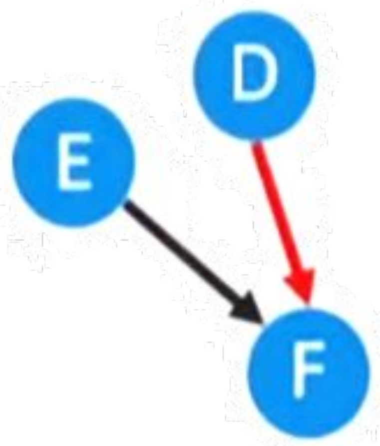
Current Node State



Current Neighbor States



Prepare "Message"



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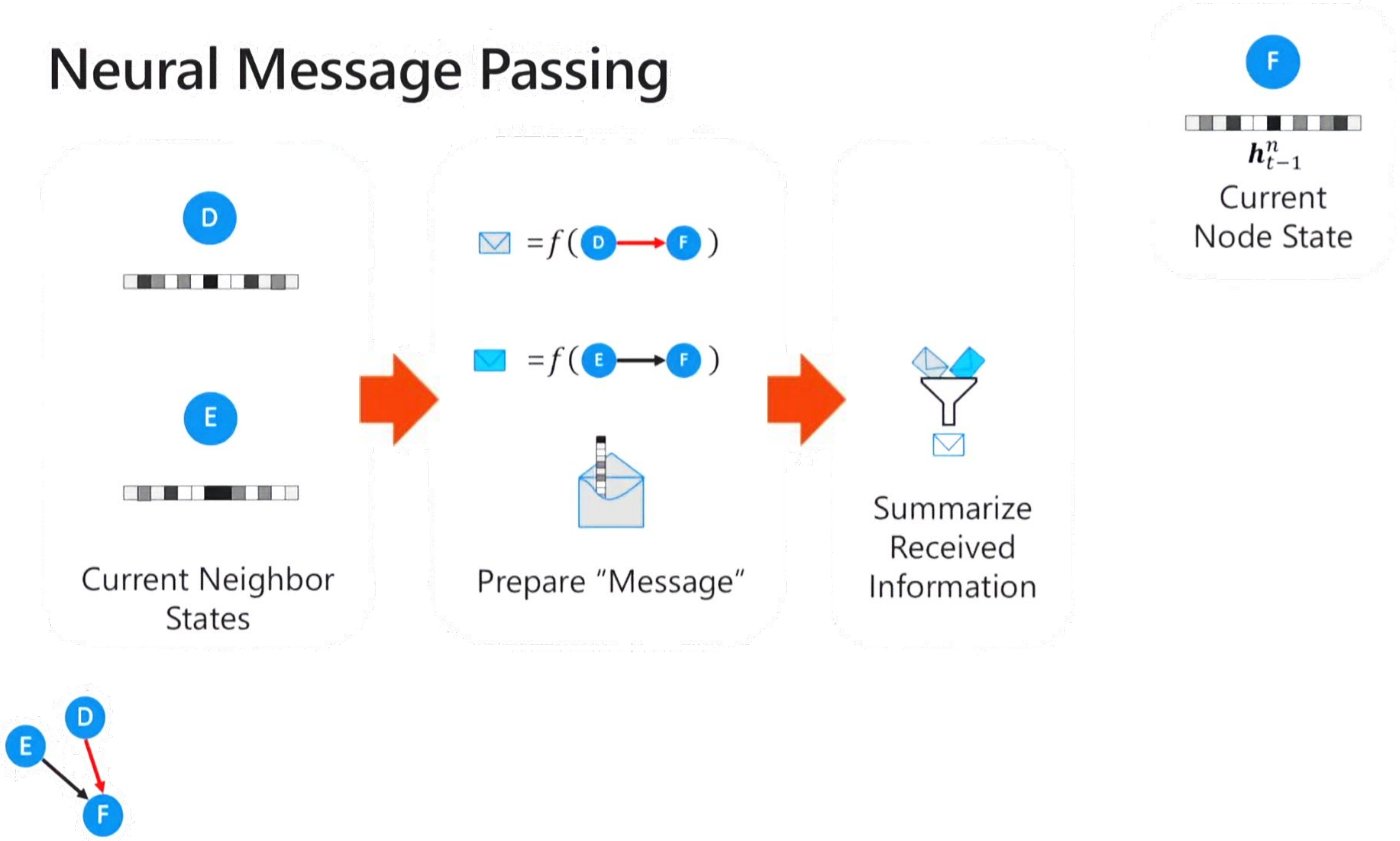

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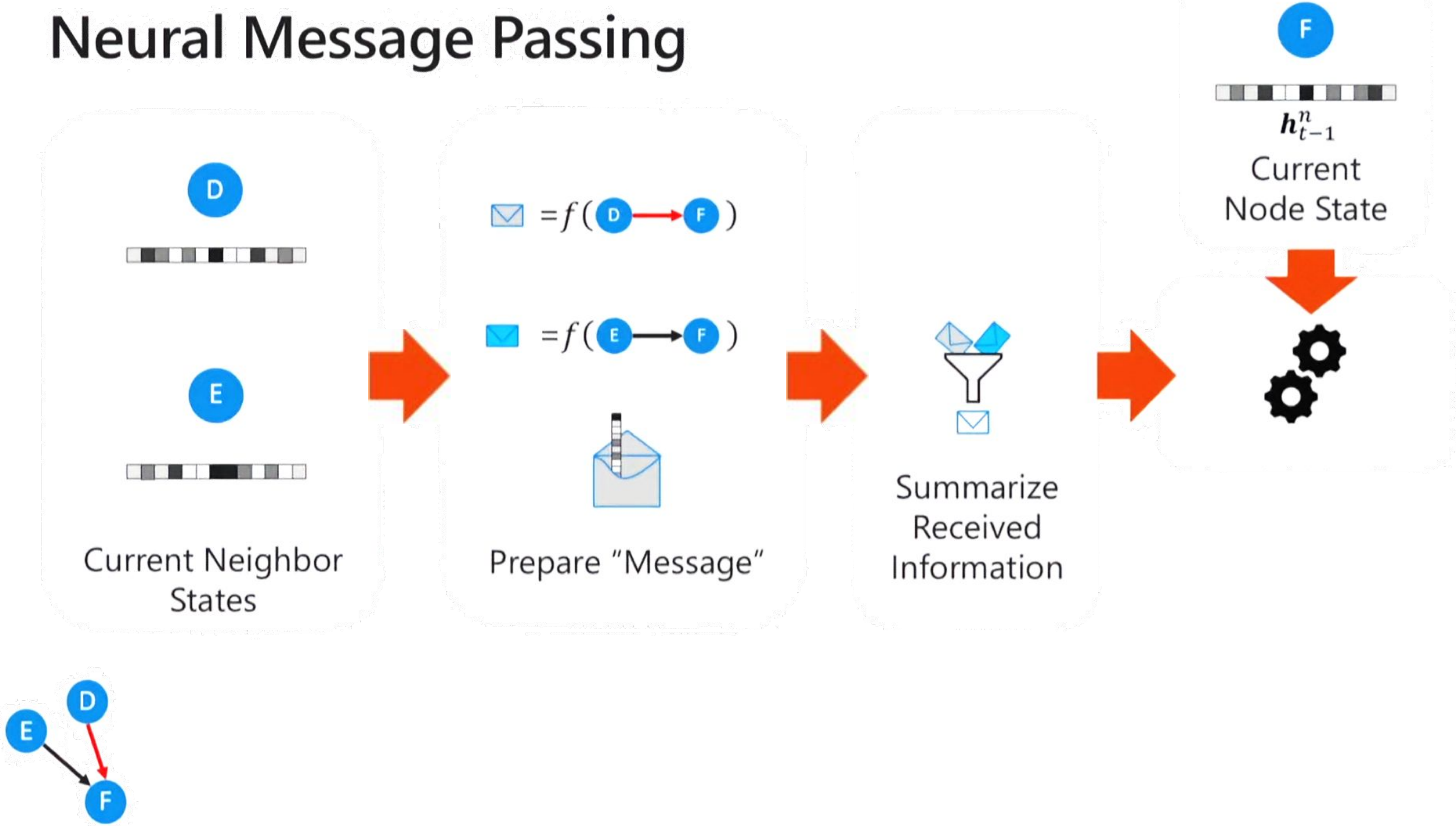

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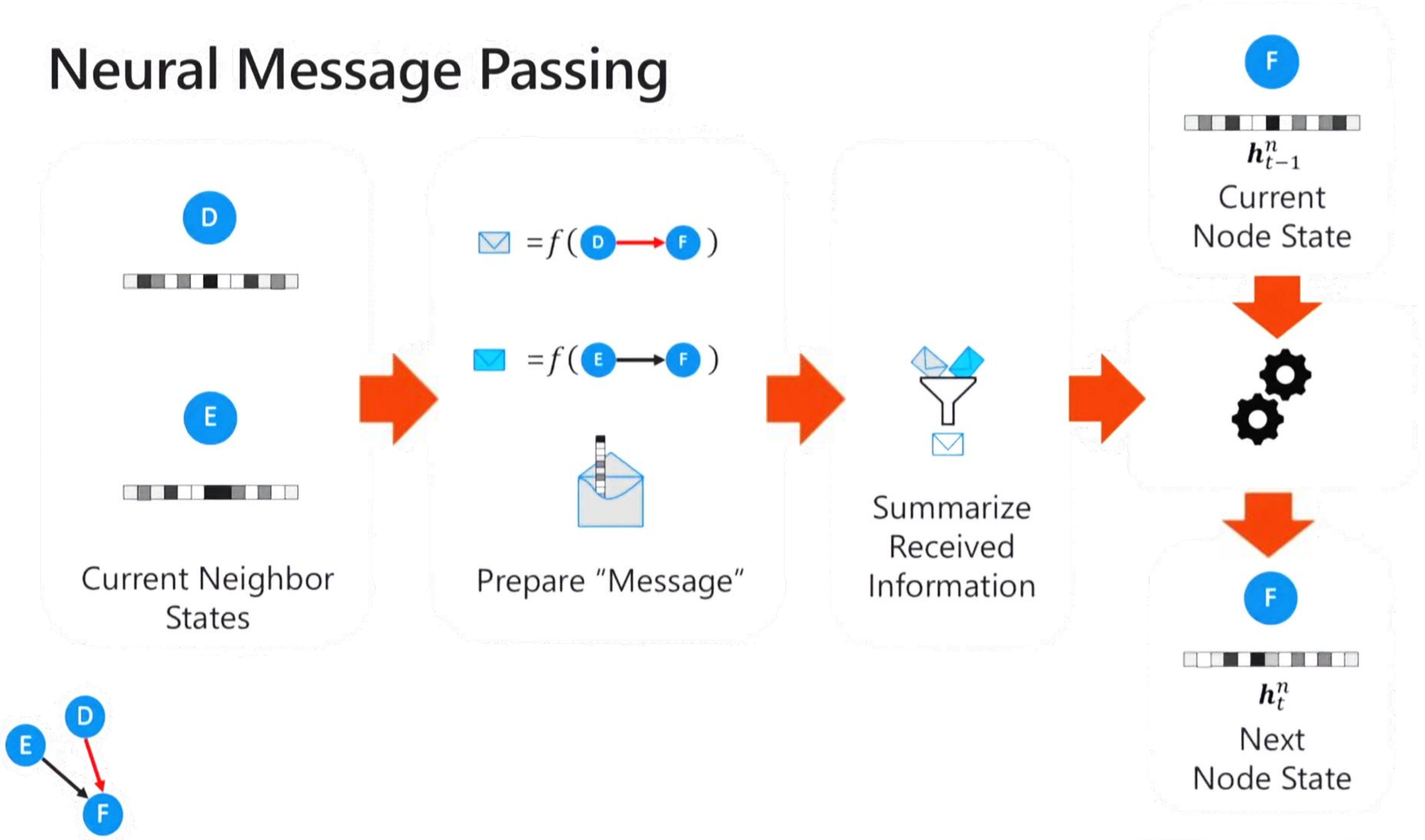

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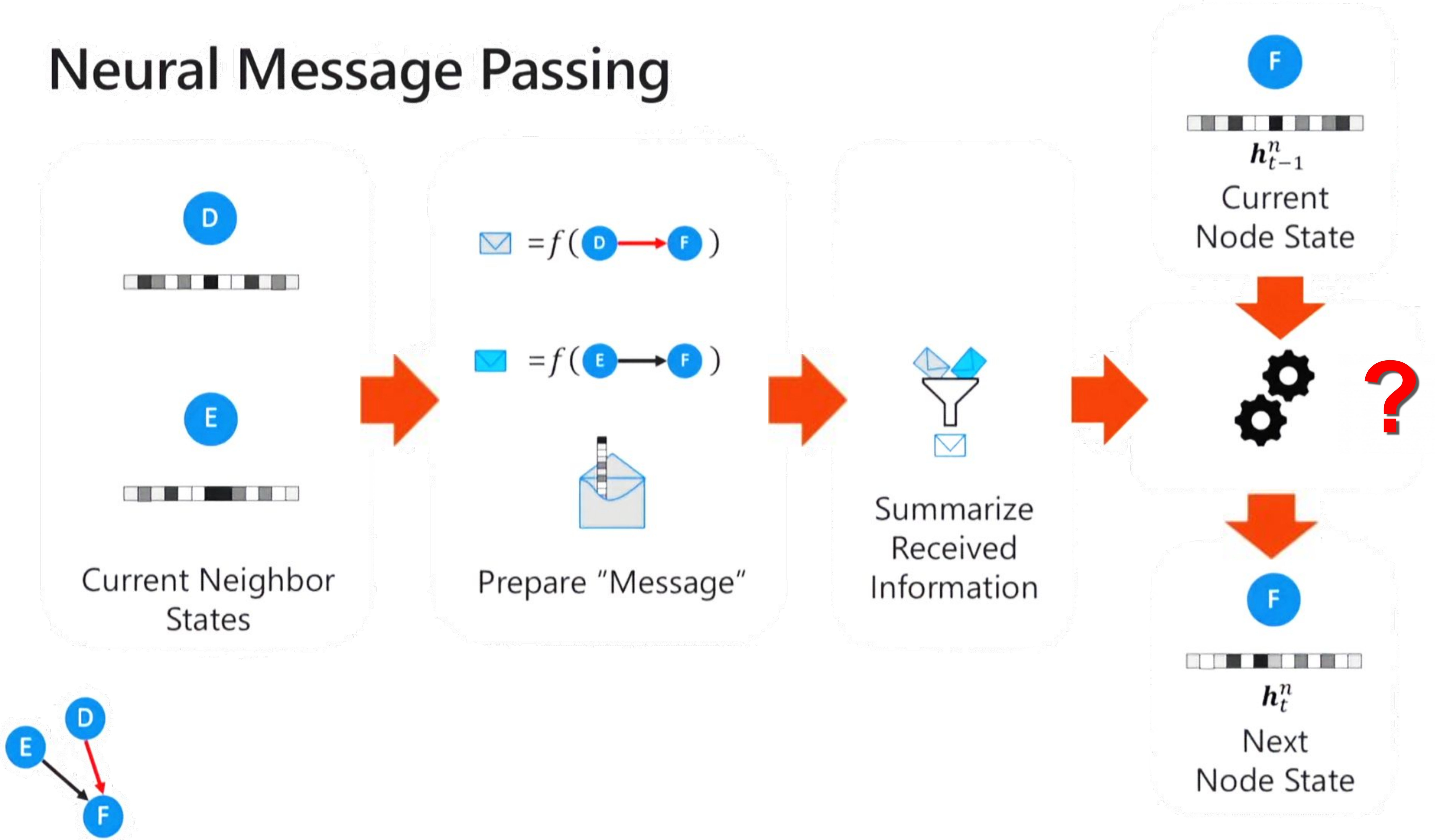
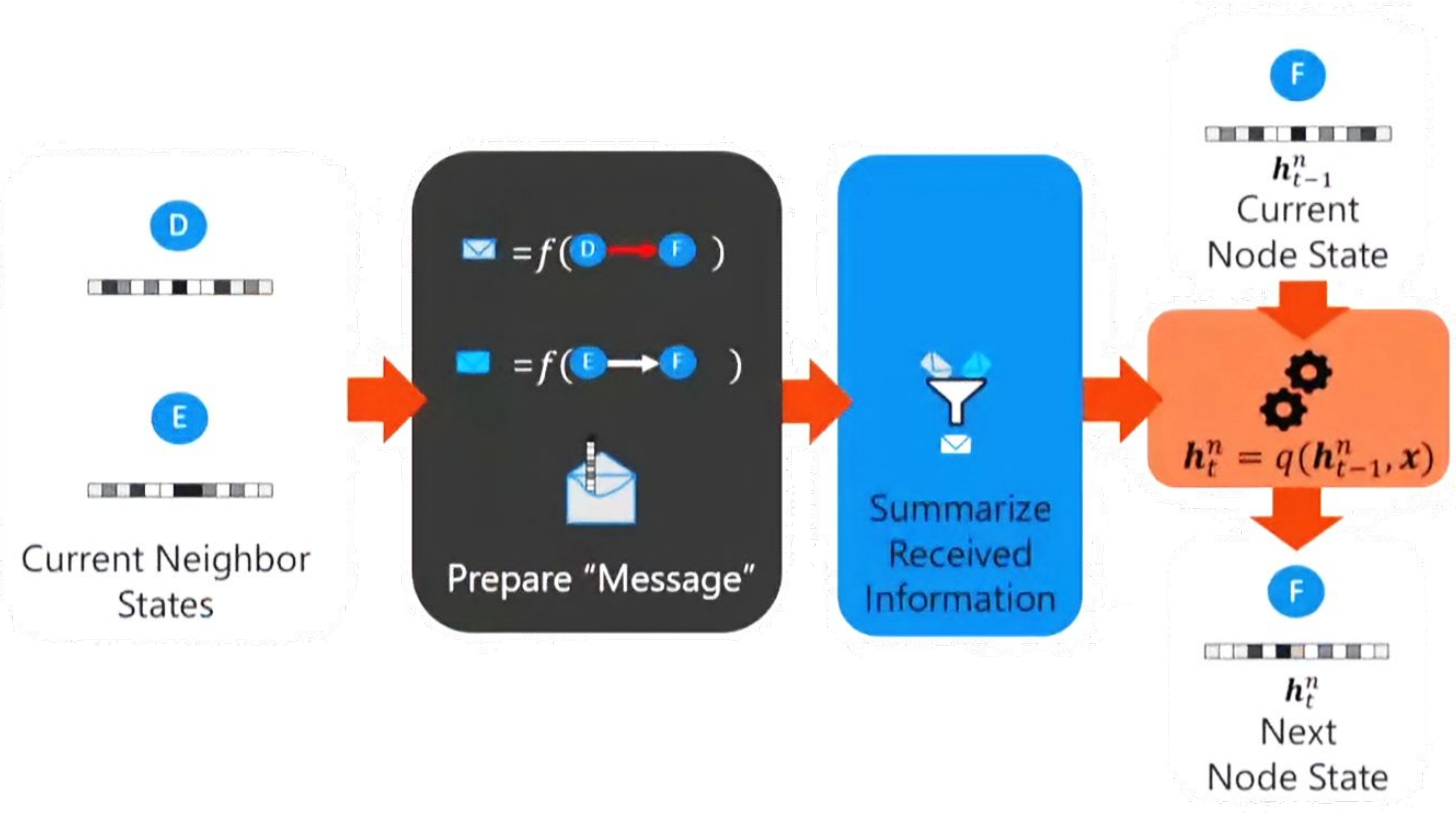
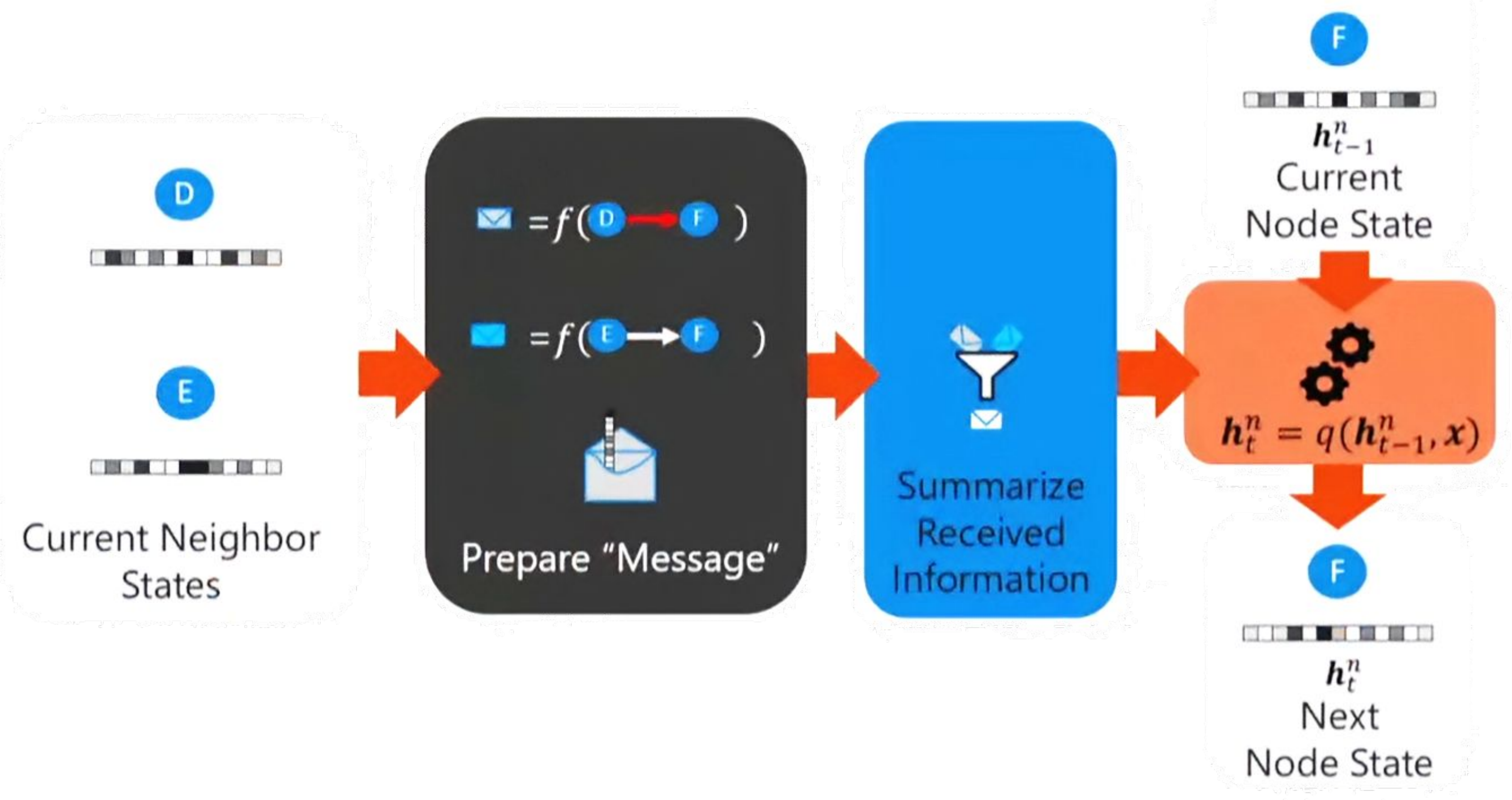
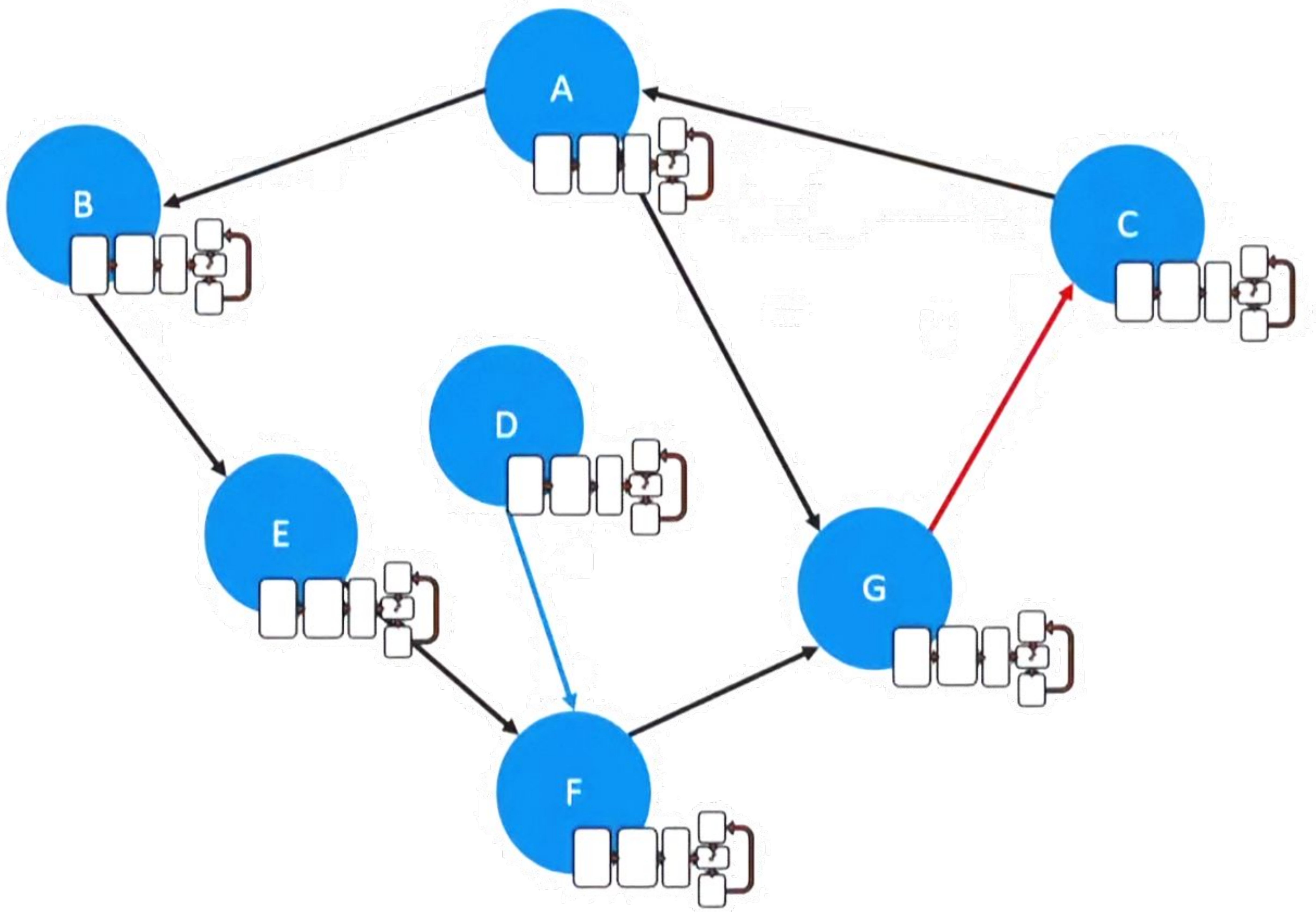


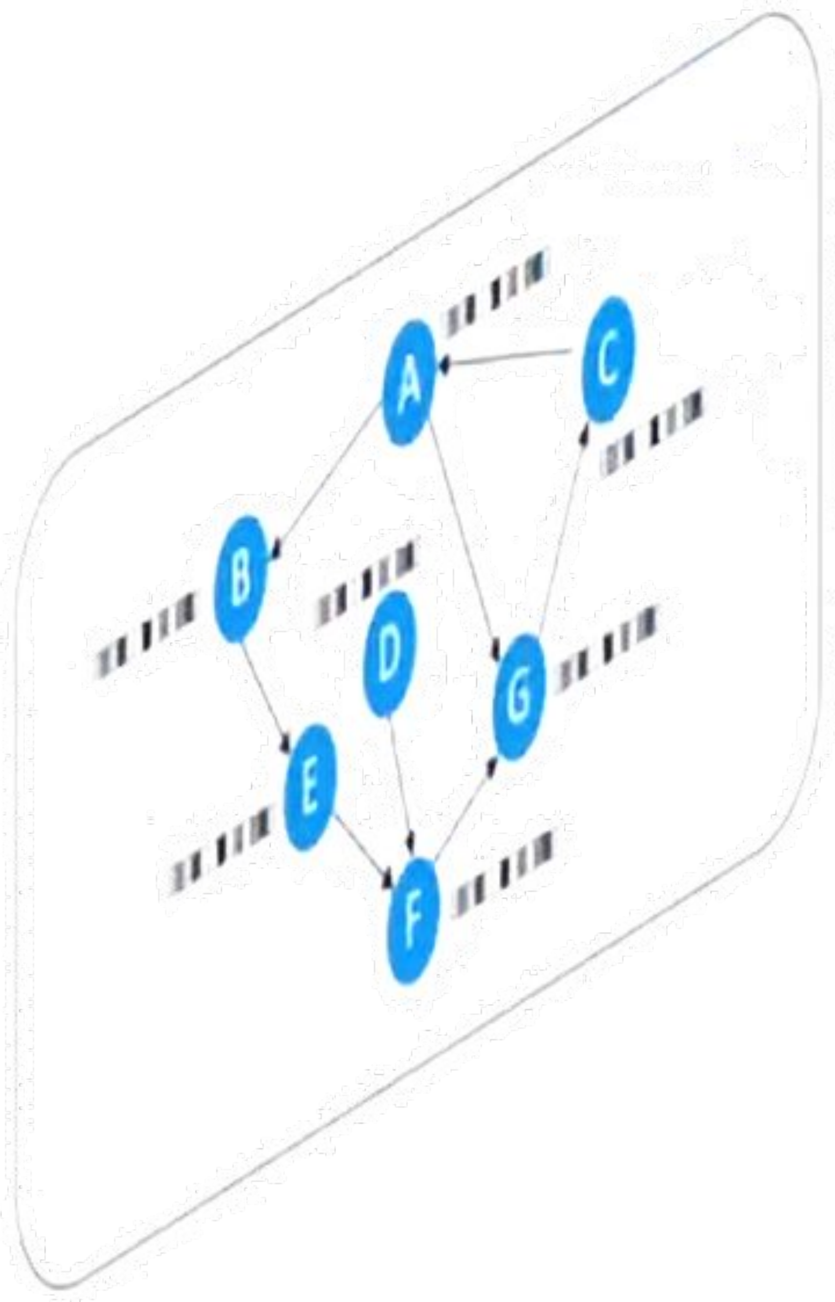

D
E
Current Neighbor States
$= f($D → F$)$
$= f($E → F$)$
Prepare "Message"
Summarize Received Information
F
h_{t-1}^n
Current Node State
$h_t^n = q(h_{t-1}^n, x)$
F
h_t^n
Next Node State



$$h^n_t = q\left(h^n_{t-1}, \bigcup_{\forall n_j : n \xrightarrow{k} n_j} f_t\left(h^n_{t-1}, k, h^{n_j}_{t-1}\right)\right)$$

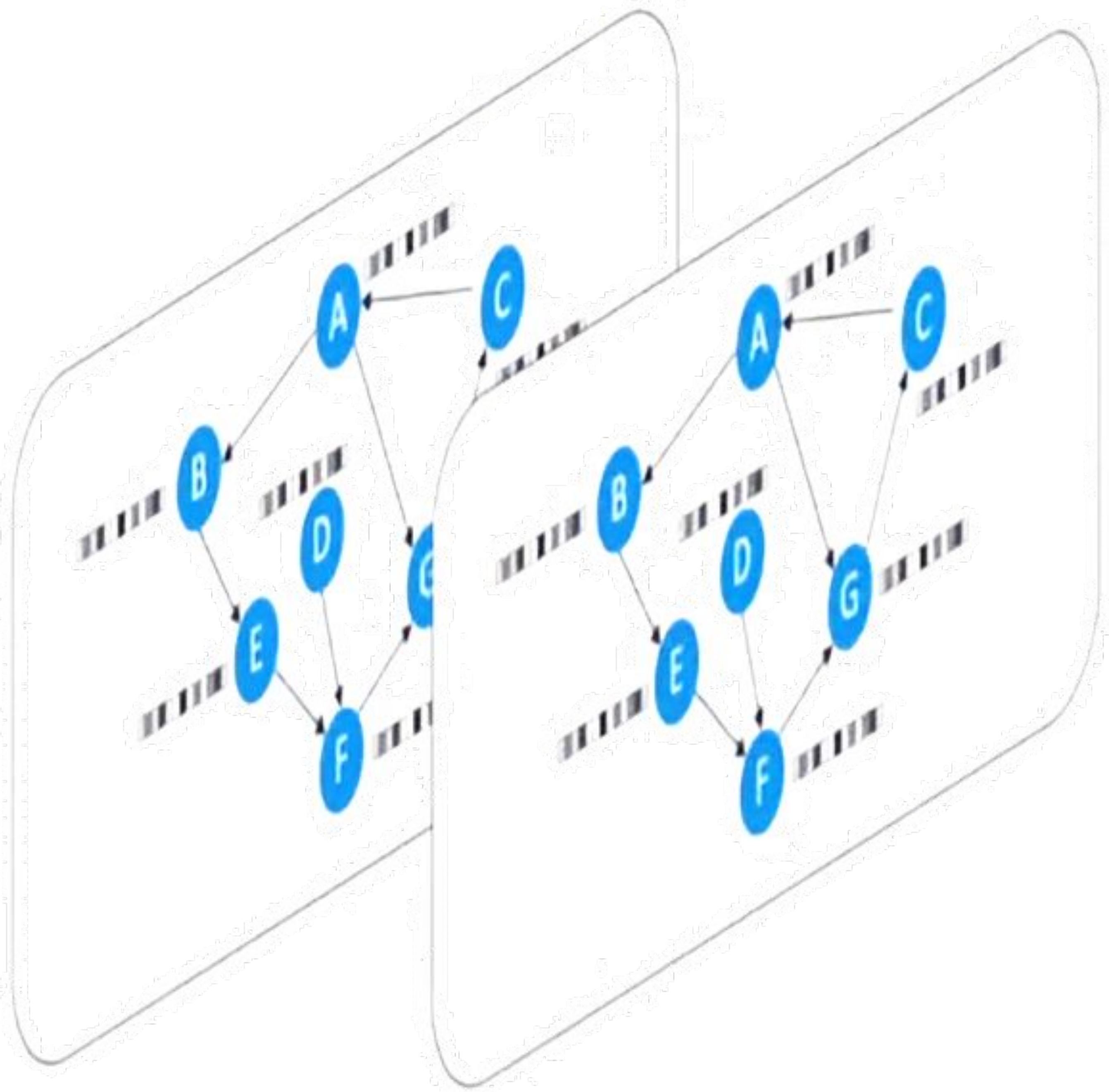

A
B
C
D
E
F
G

Graph Neural Networks: Message Passing



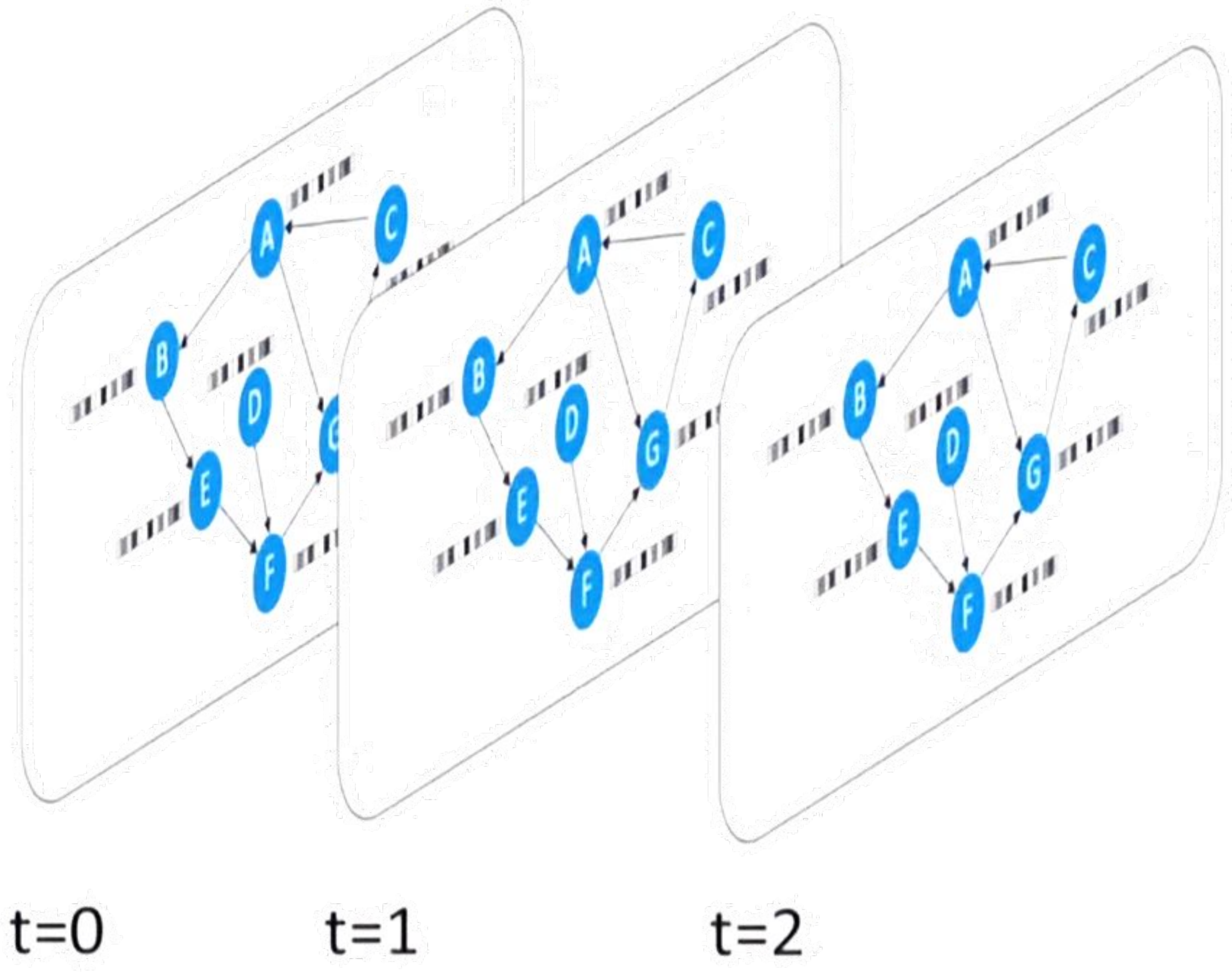
t=0

Graph Neural Networks: Message Passing



t=0 t=1

Graph Neural Networks: Message Passing



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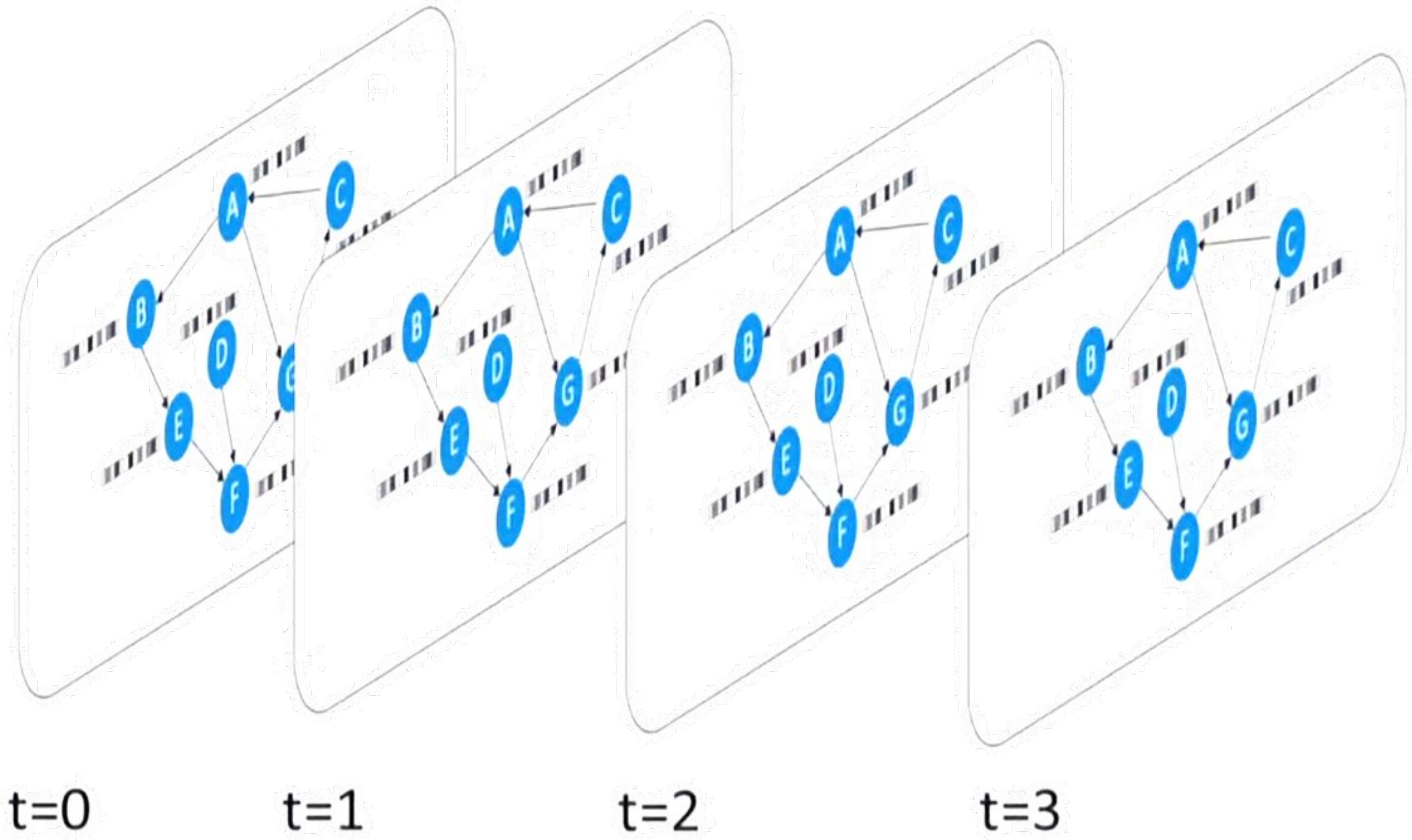

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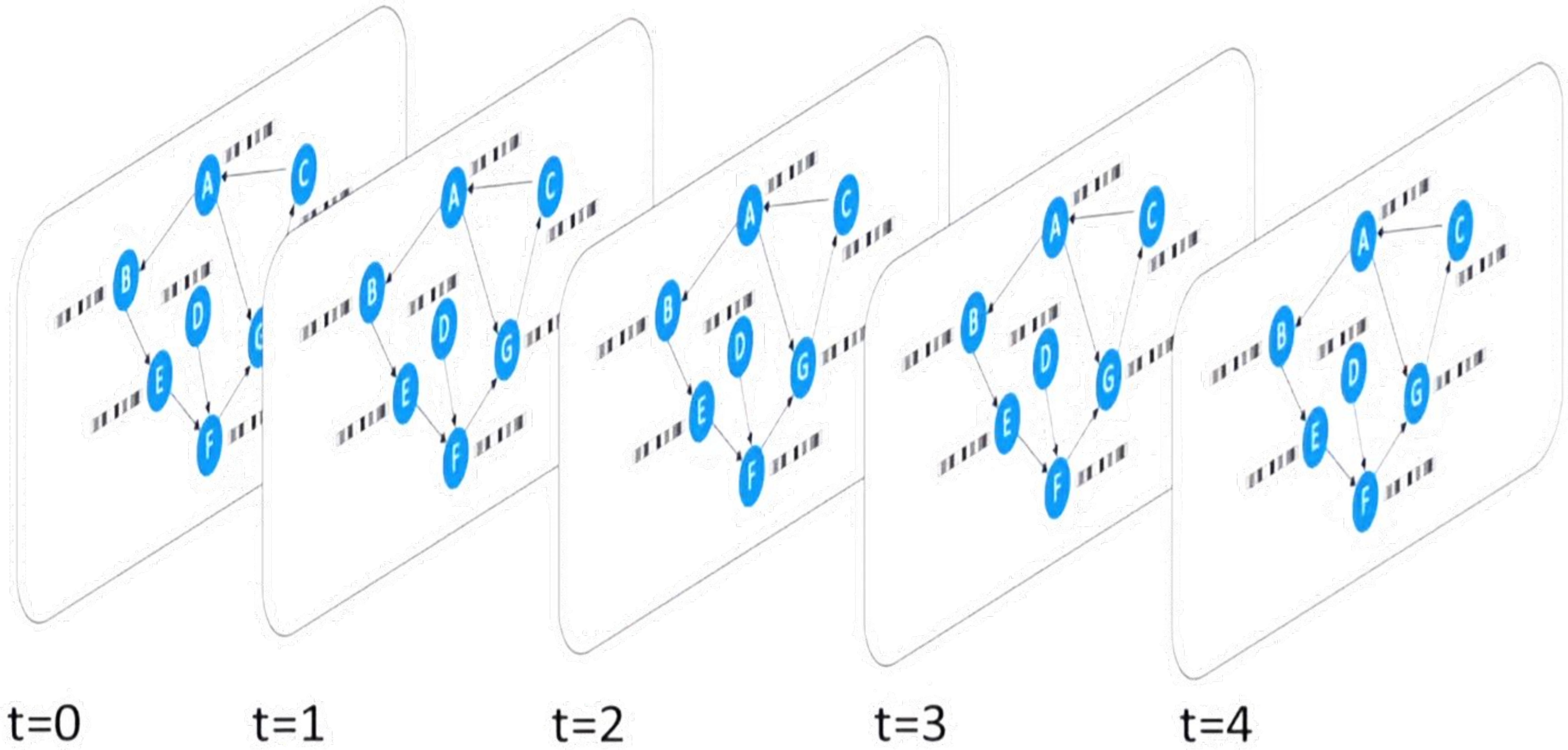
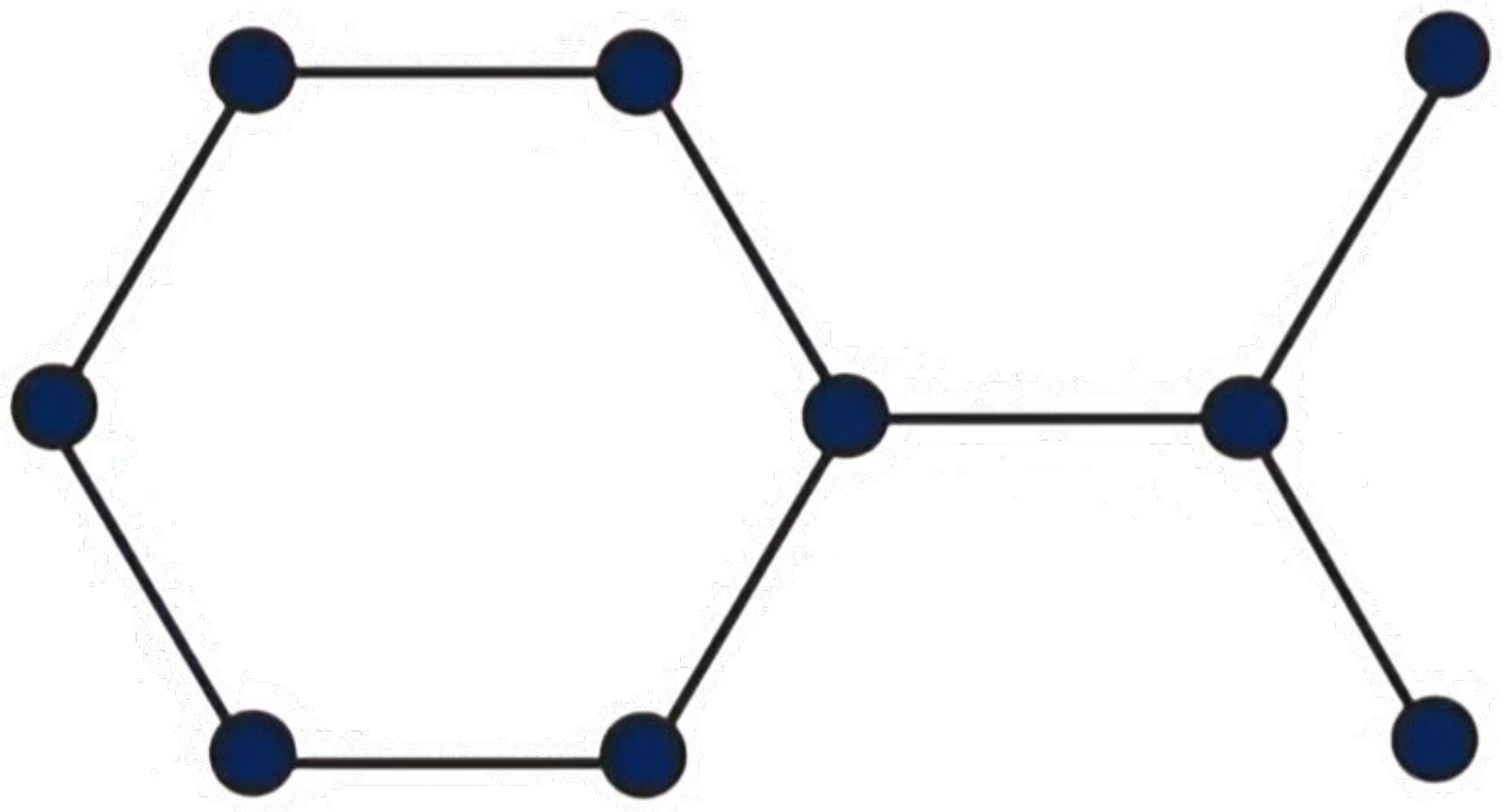


GNNs: Synchronous Message Passing (All-to-All)



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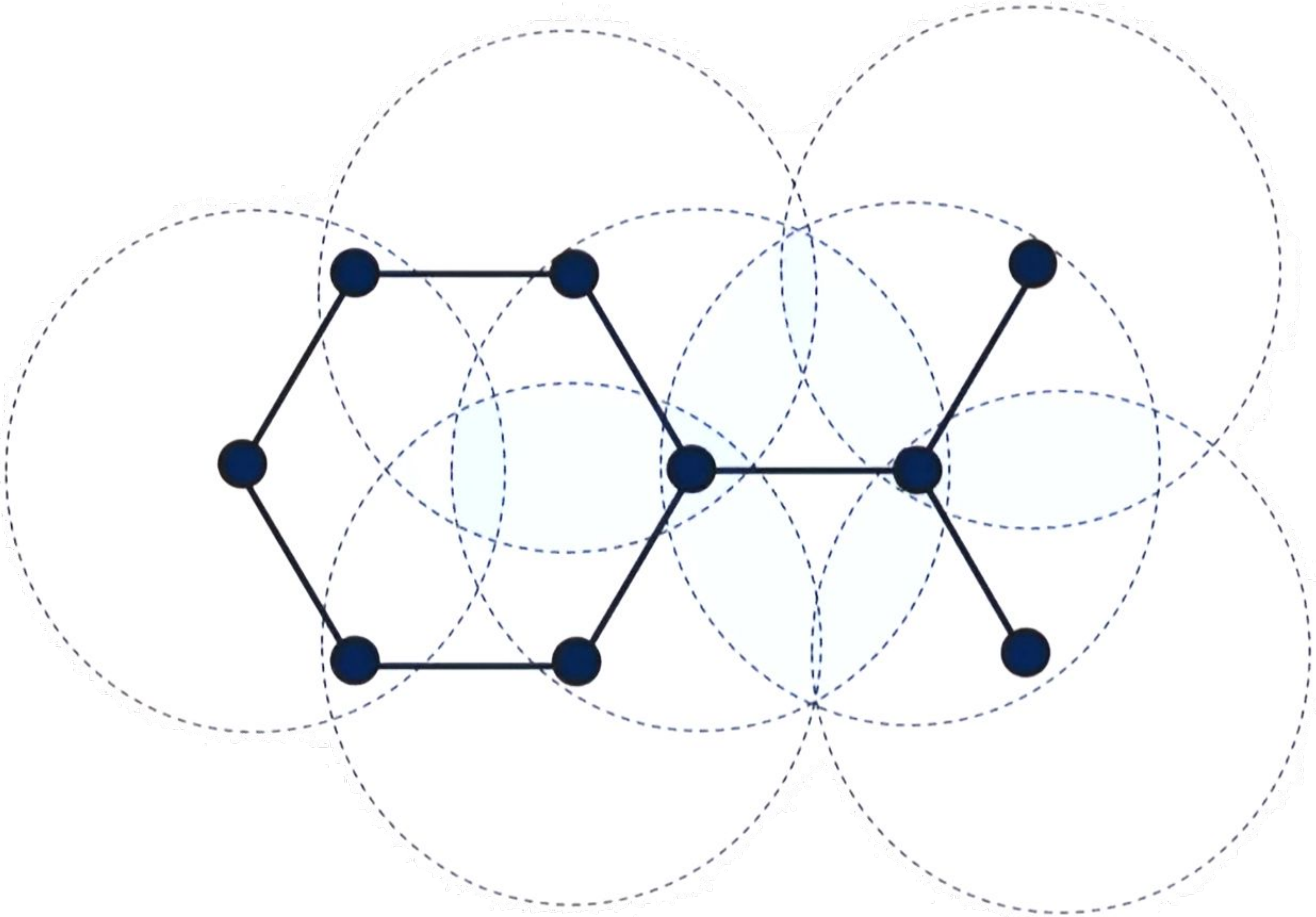

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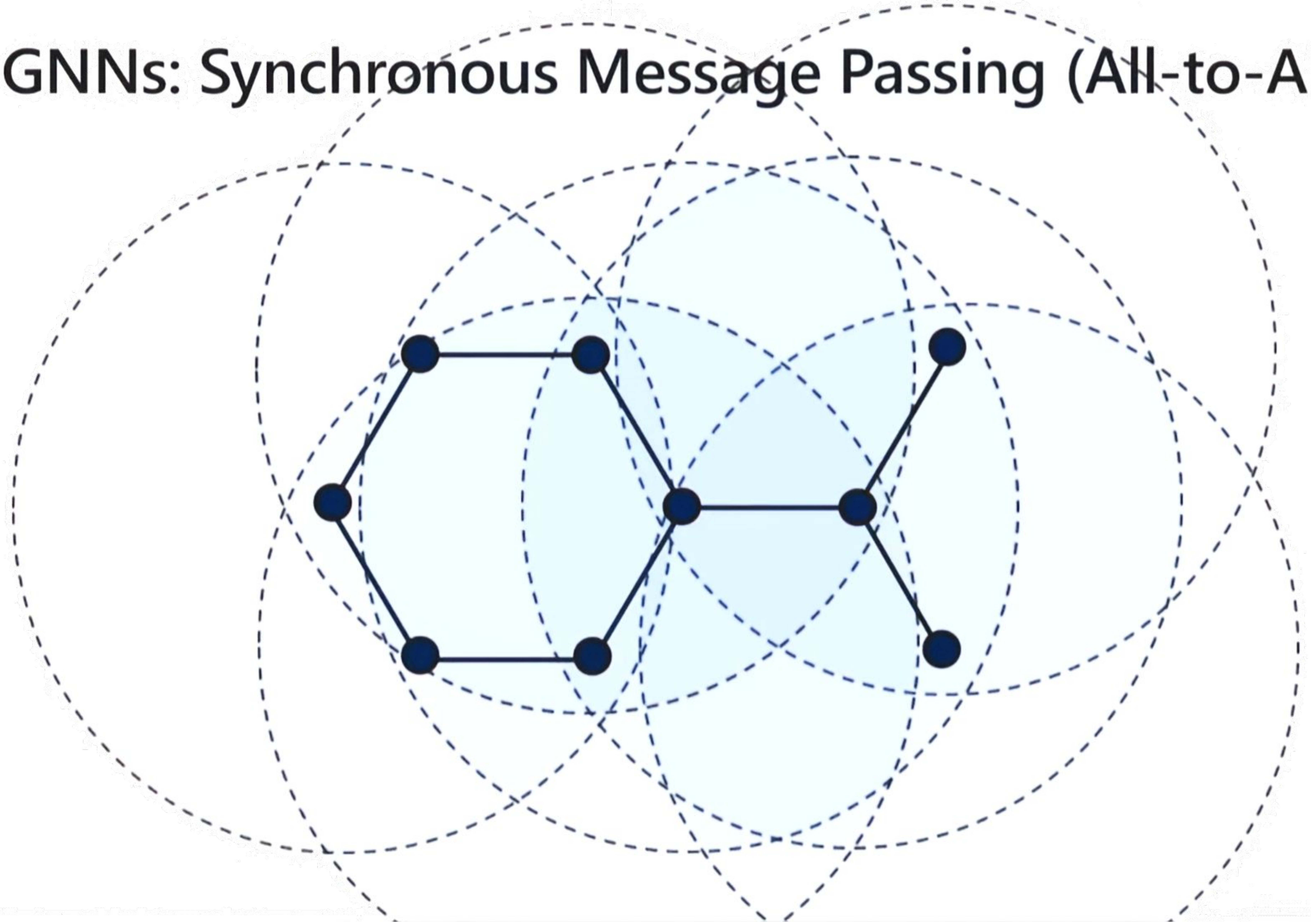
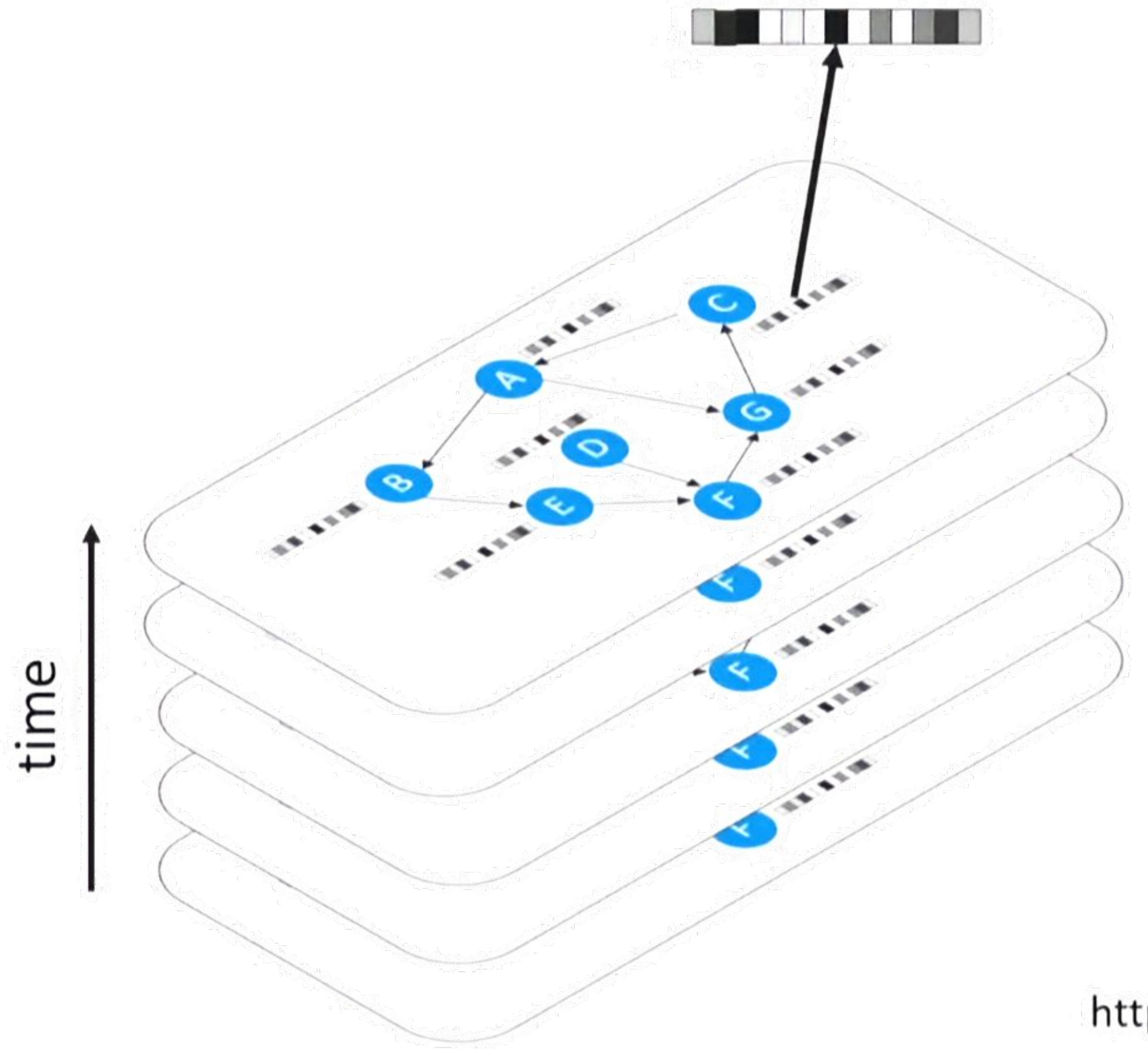


Graph Neural Networks: Output



- node selection
- node classification
- graph classification

https://github.com/microsoft/tf-gnn-samples/

Perception

The perceptual capabilities of robots encompass a variety of skills:

- State estimation
- Segmentation
- Tracking
- Recognition
- Classification

Perception

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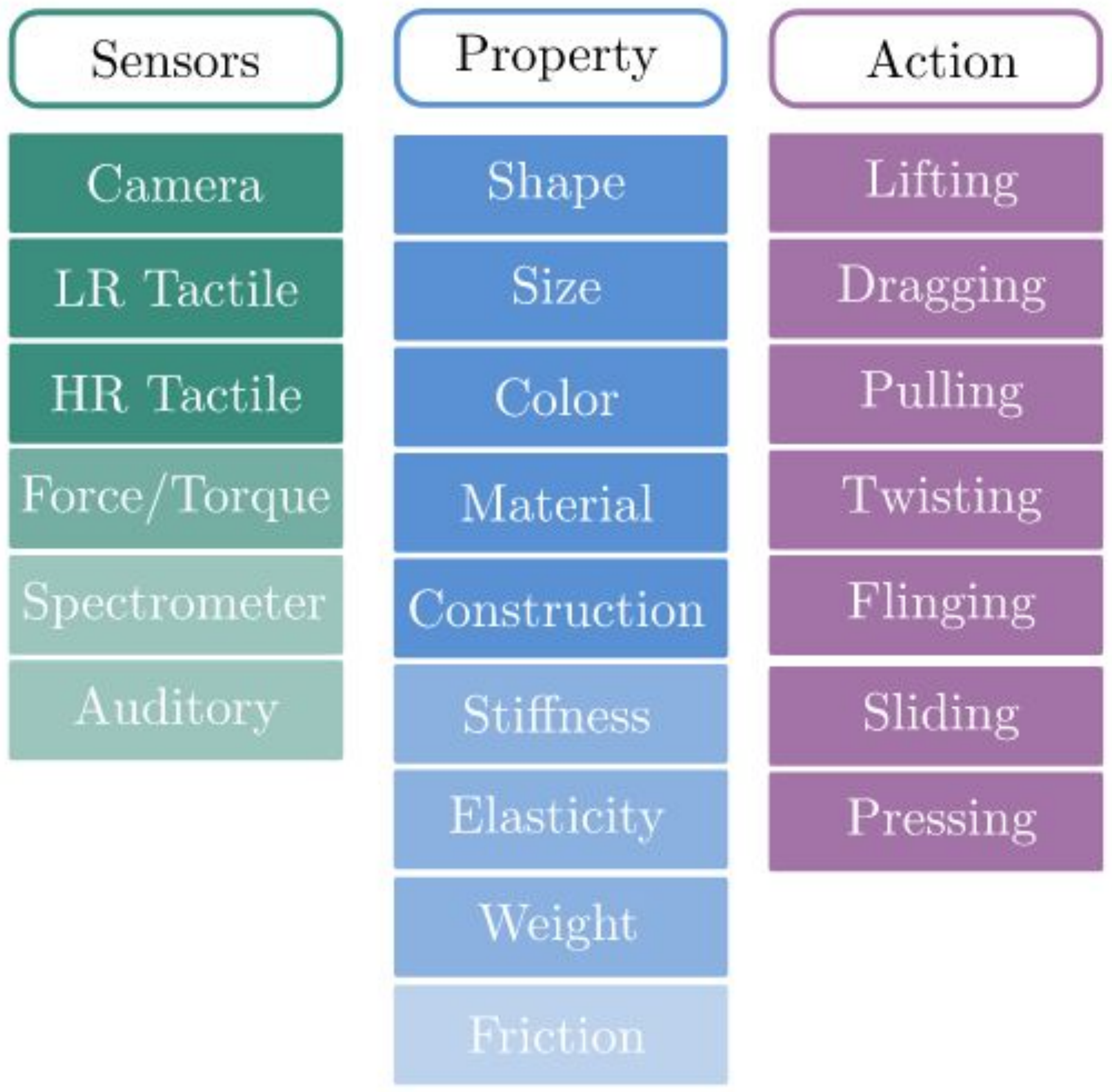
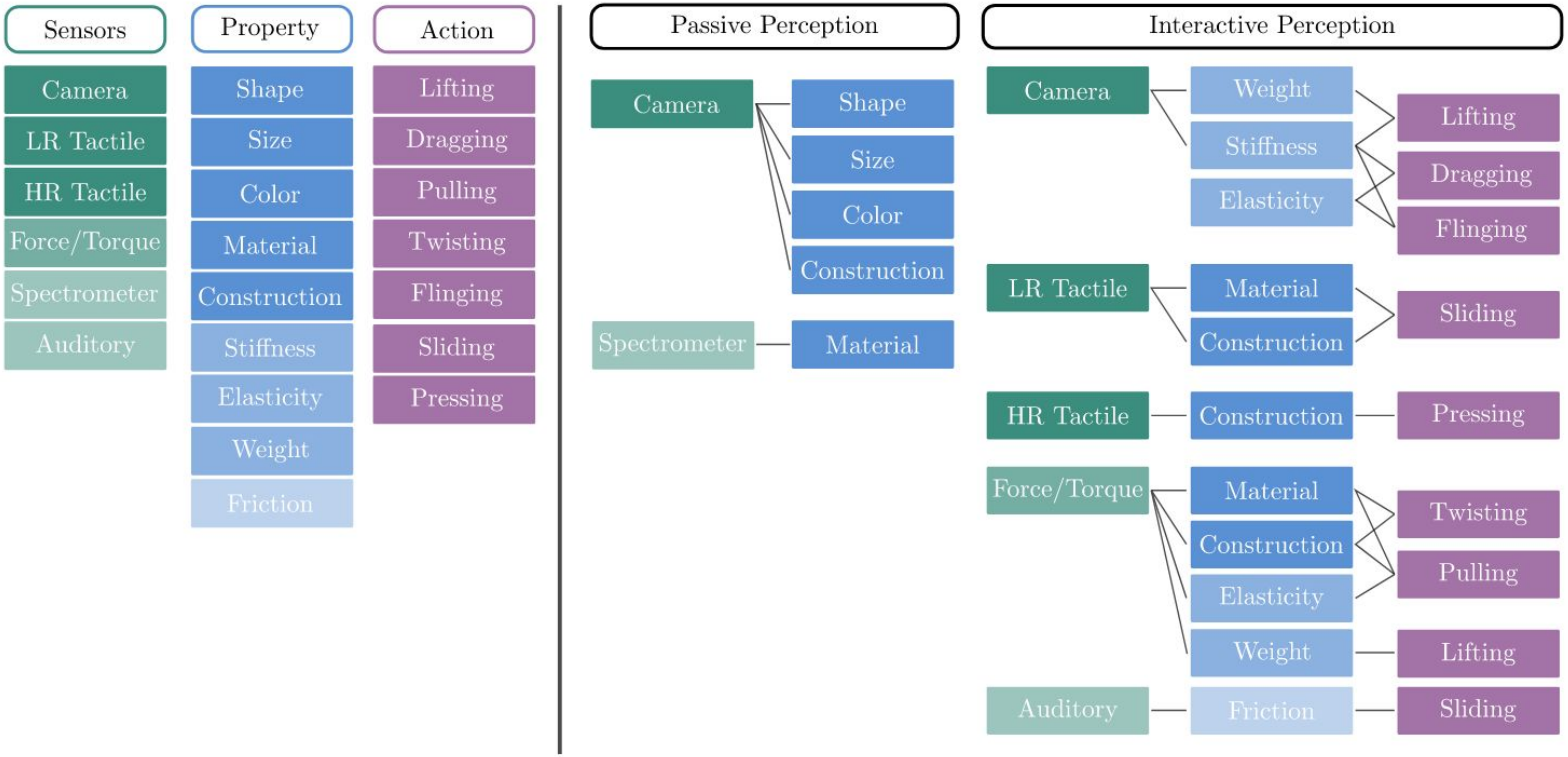
How do we get these data?

Properties Perception



Properties Perception



Garcia-Camacho I, Borr`as J, Calli B, Norton A, Alenya` G. 2022. Household cloth object set: Fostering benchmarking in deformable object manipulation. IEEE Robotics Autom. Lett. 7(3):5866–73

Representation and State Estimation

State estimation of a deformable object x can be seen as
An optimization problem based on observations *o* and object representation M(·)

$$x^* = \arg\min_x \left\| o - \mathbf{M}(x) \right\|$$
$$x \in \text{ObjectStates}$$

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$$
\begin{aligned}
x^* &= \arg\min_x \left\| o - \mathbf{M}(x) \right\| \\
x &\in \text{ObjectStates}
\end{aligned}
$$

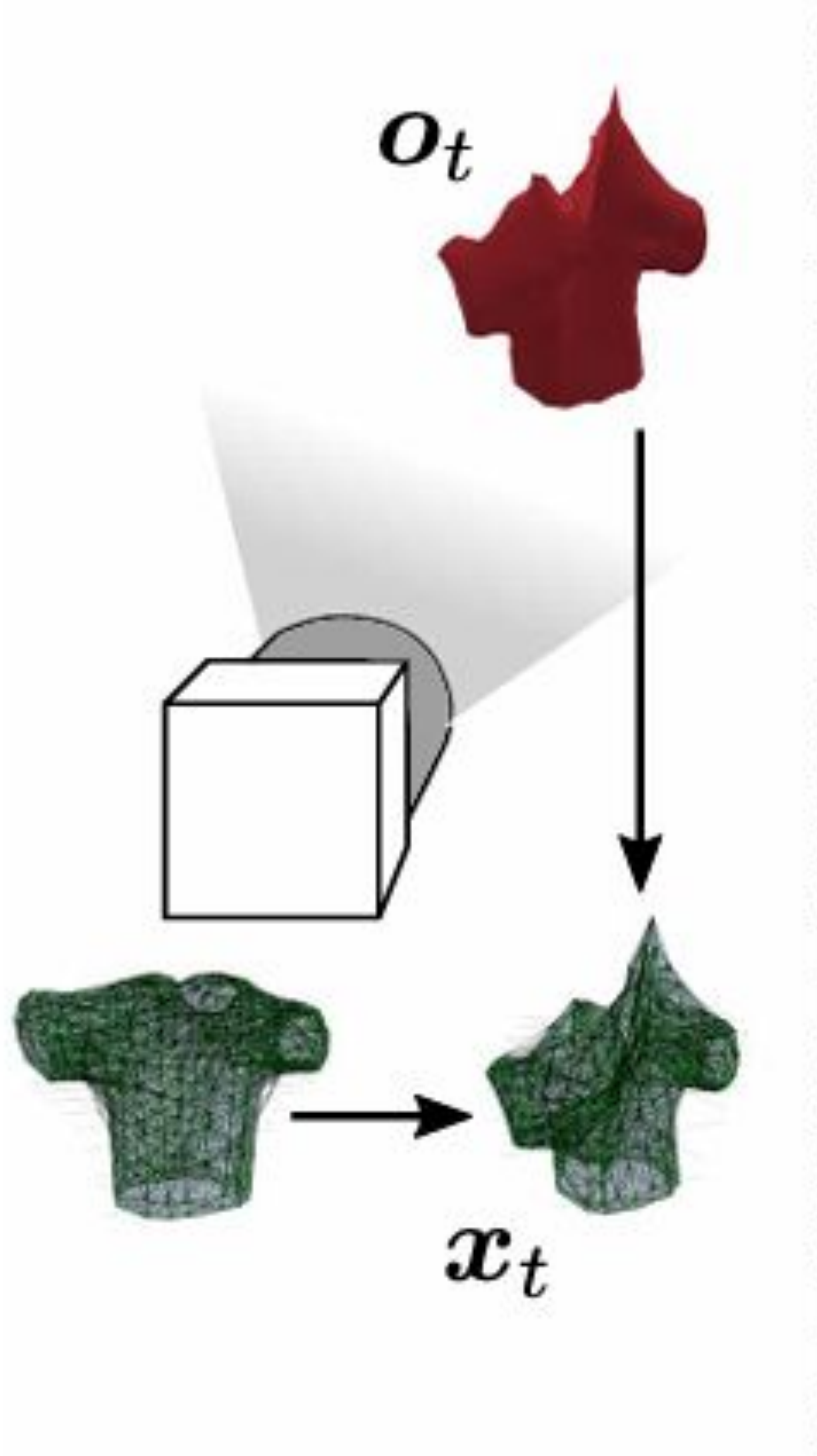
The estimation problem may be formulated as

$$
\begin{aligned}
\theta^* &= \arg\min_\theta \sum_t \left\| o_t - \mathbf{M}_t(\hat{x}_t) \right\| \\
\hat{x}_{t+1} &= \text{ObjectDynamics}(\hat{x}_t, f_t, \theta)
\end{aligned}
$$

where $\hat{x}$ is the predicted state that depends on object parameters
such as material properties θ and applied forces f

Garcia-Camacho I, Borr`as J, Calli B, Norton A, Alenya` G. 2022. Household cloth object set: Fostering benchmarking in deformable object manipulation. IEEE Robotics Autom. Lett. 7(3):5866–73

Deformable Object Perception Tasks



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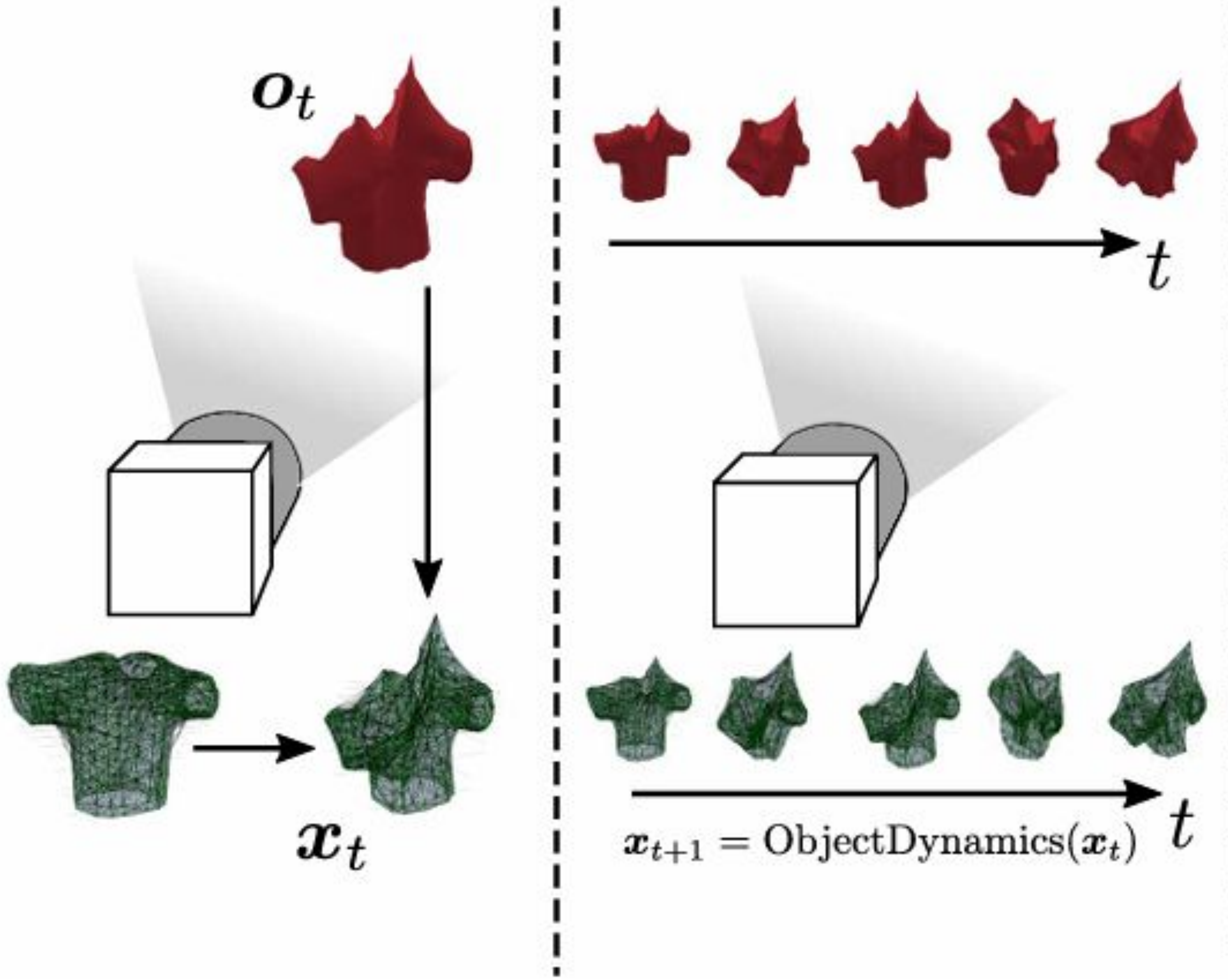
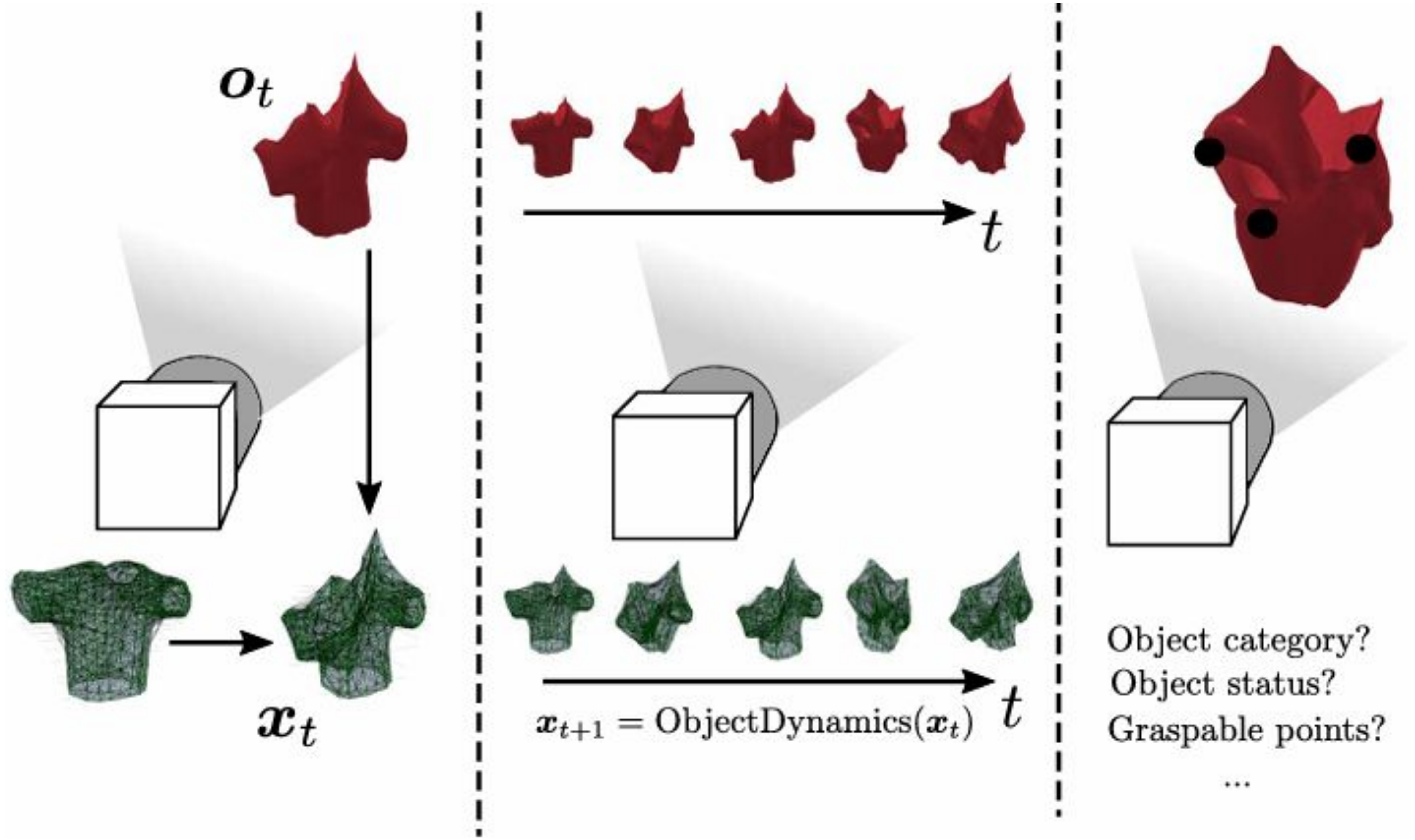
Deformable Object Perception Tasks



Garcia-Camacho I, Borr`as J, Calli B, Norton A, Alenya` G. 2022. Household cloth object set: Fostering benchmarking in deformable object manipulation. IEEE Robotics Autom. Lett. 7(3):5866–73

Deformable Object Perception Tasks



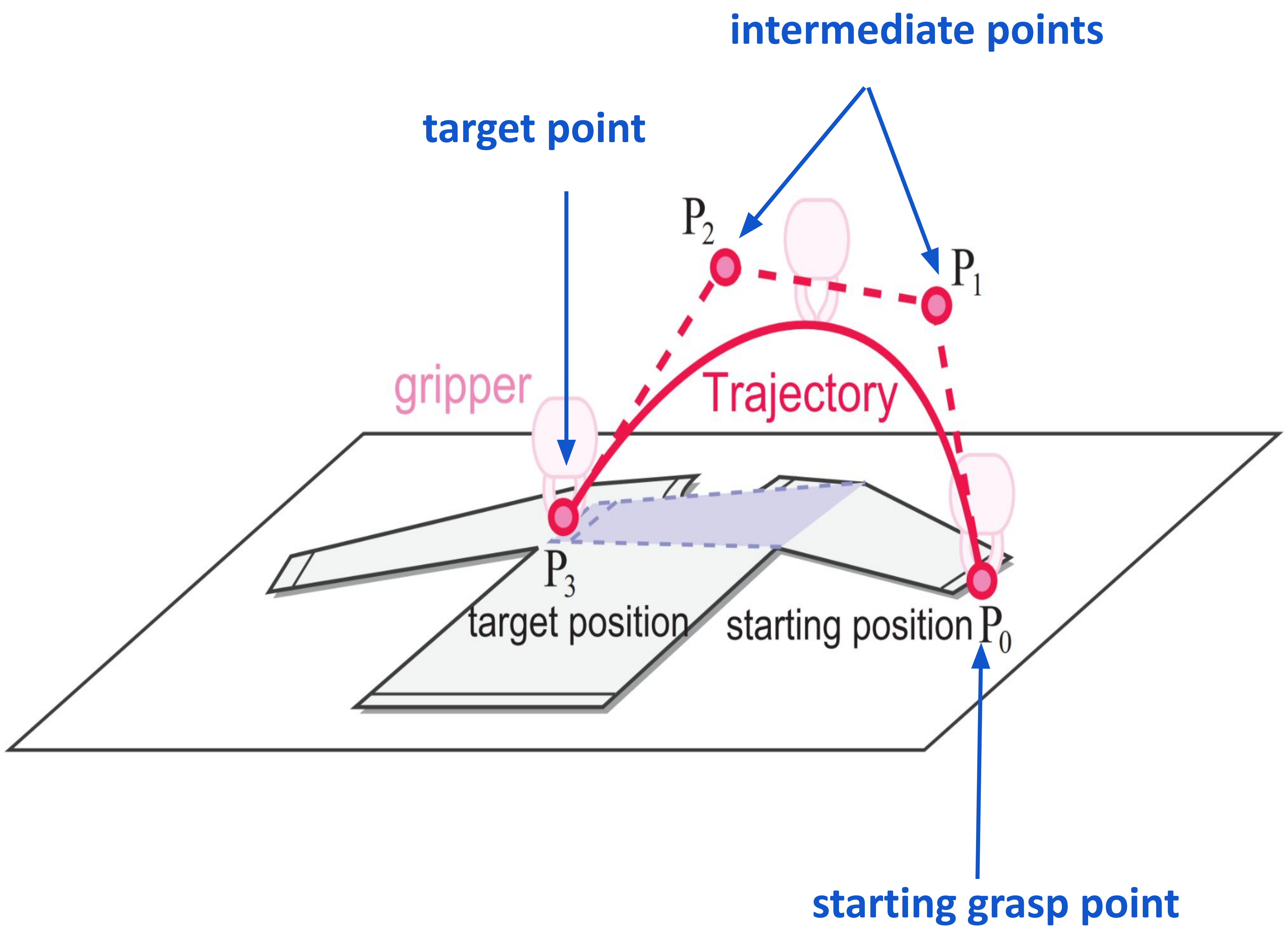
Garcia-Camacho I, Borr`as J, Calli B, Norton A, Alenya` G. 2022. Household cloth object set: Fostering benchmarking in deformable object manipulation. IEEE Robotics Autom. Lett. 7(3):5866–73

Manipulation

Problem Definition

Task: Fold the sleeve into blue target position

Use a robotic manipulator to grasp the sleeve at P_o and move to target point P_3



Li, Y., Yue, Y., Xu, D., Grinspun, E., & Allen, P. K. (2015). Folding deformable objects using predictive simulation and trajectory optimization. 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 6000–6006. doi:10.1109/IROS.2015.7354231

Mathematical Formulation

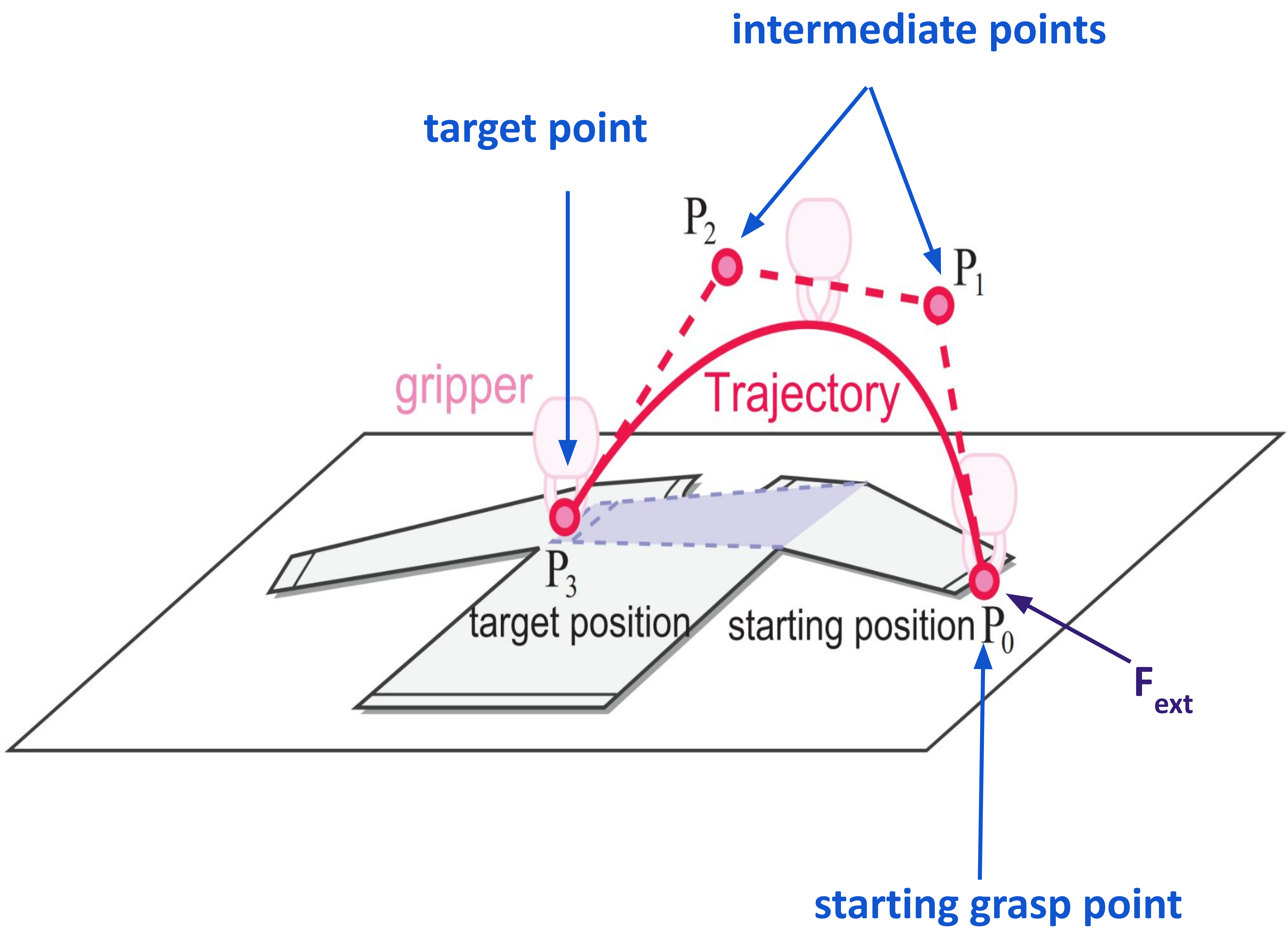
Goal: To find

a) external force F_{ext} (acting on the cloth)

OR

b) motion of the grasp point (P_0, P_1, P_2, P_3)

in order to achieve the target position of sleeve

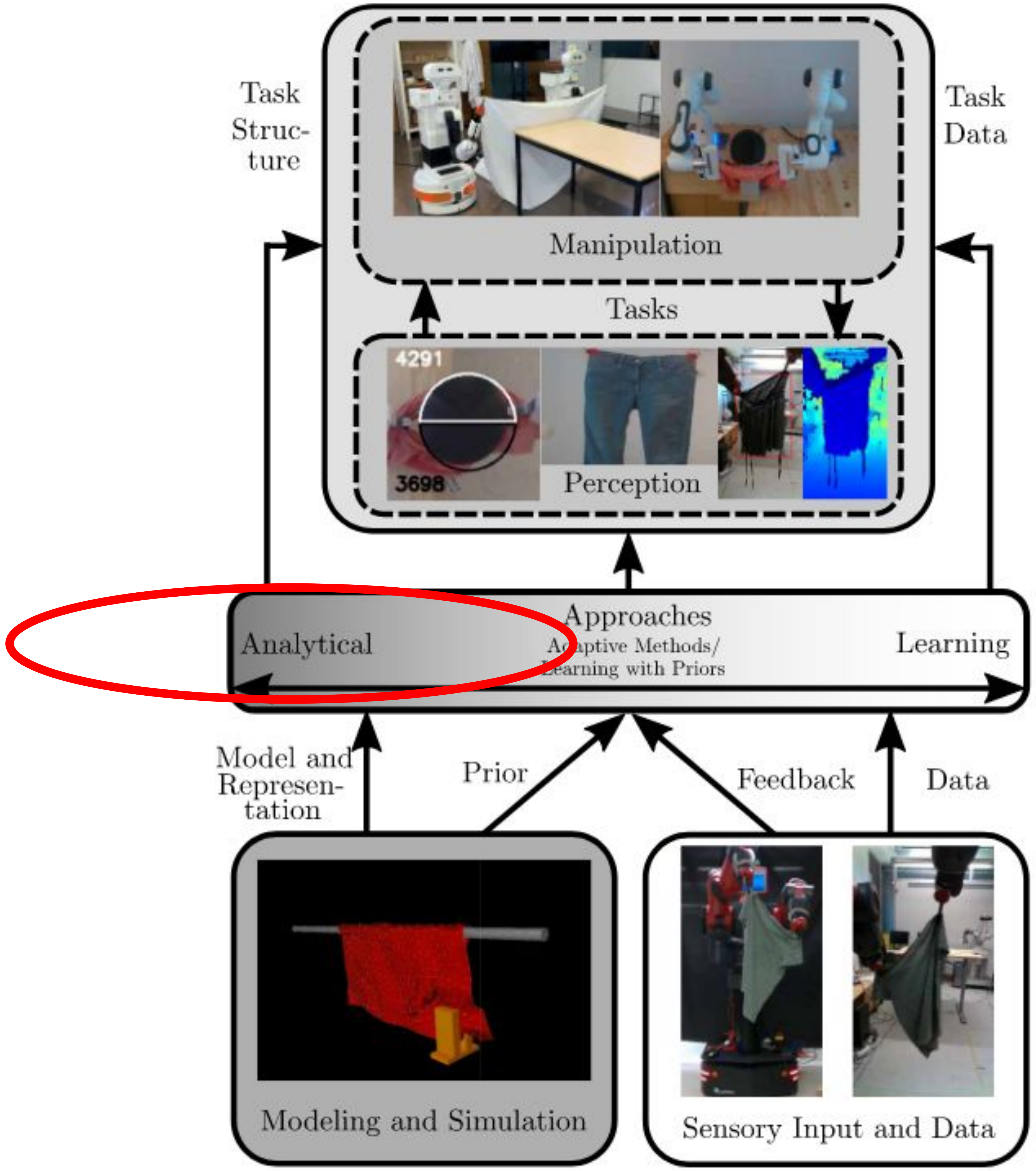


(4 points assumed for the sake of simplicity)

Li, Y., Yue, Y., Xu, D., Grinspun, E., & Allen, P. K. (2015). Folding deformable objects using predictive simulation and trajectory optimization. 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 6000–6006. doi:10.1109/IROS.2015.7354231

How can we solve this?

Recap



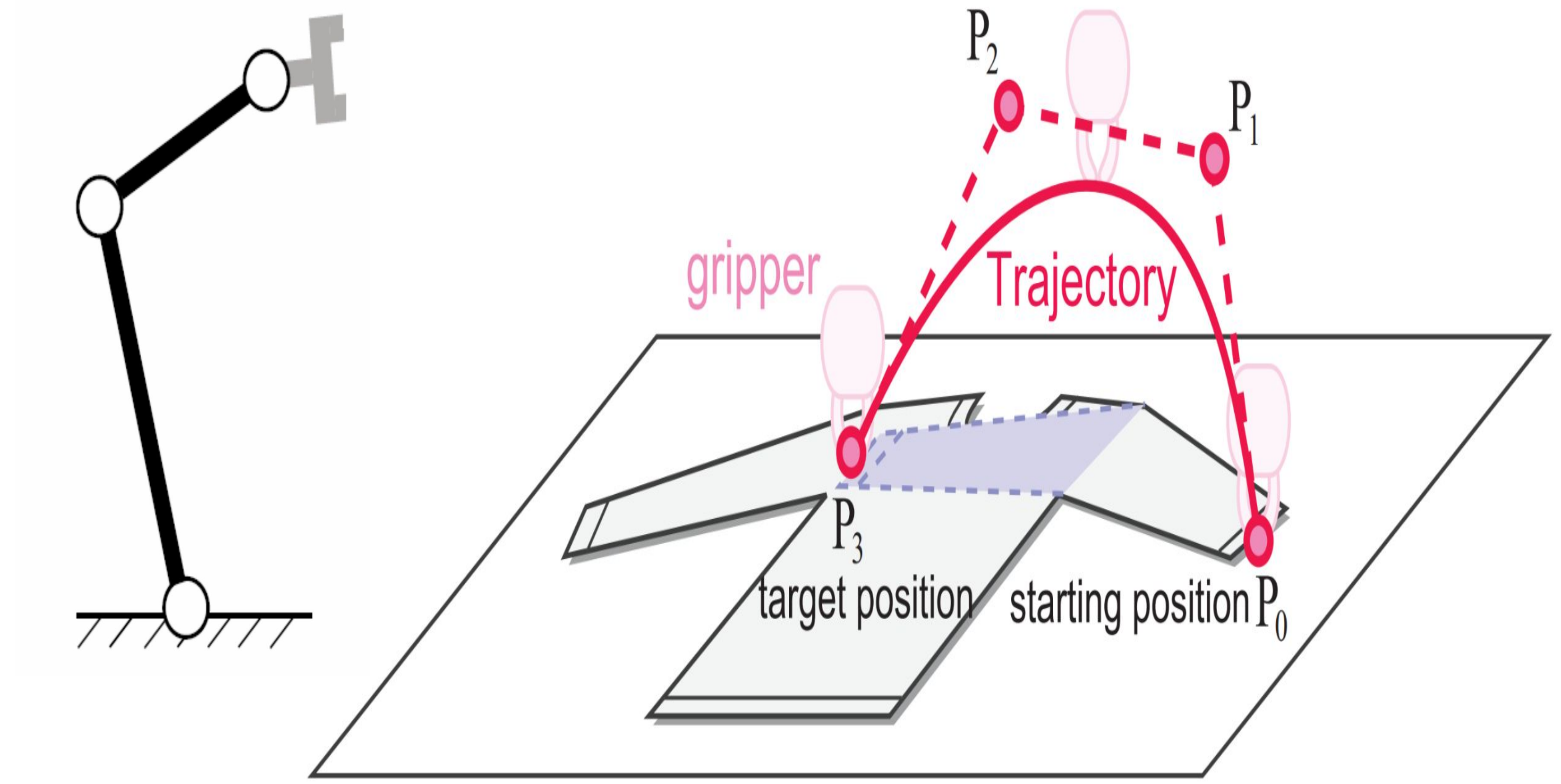
"Modeling, learning, perception, and control methods for deformable object manipulation.", Yin, Hang, Anastasia Varava, and Danica Kragic, Science Robotics 6.54 (2021)

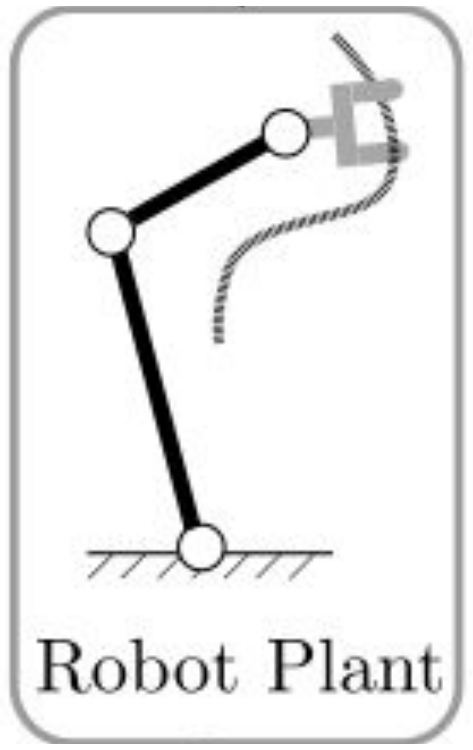
How can we solve this?

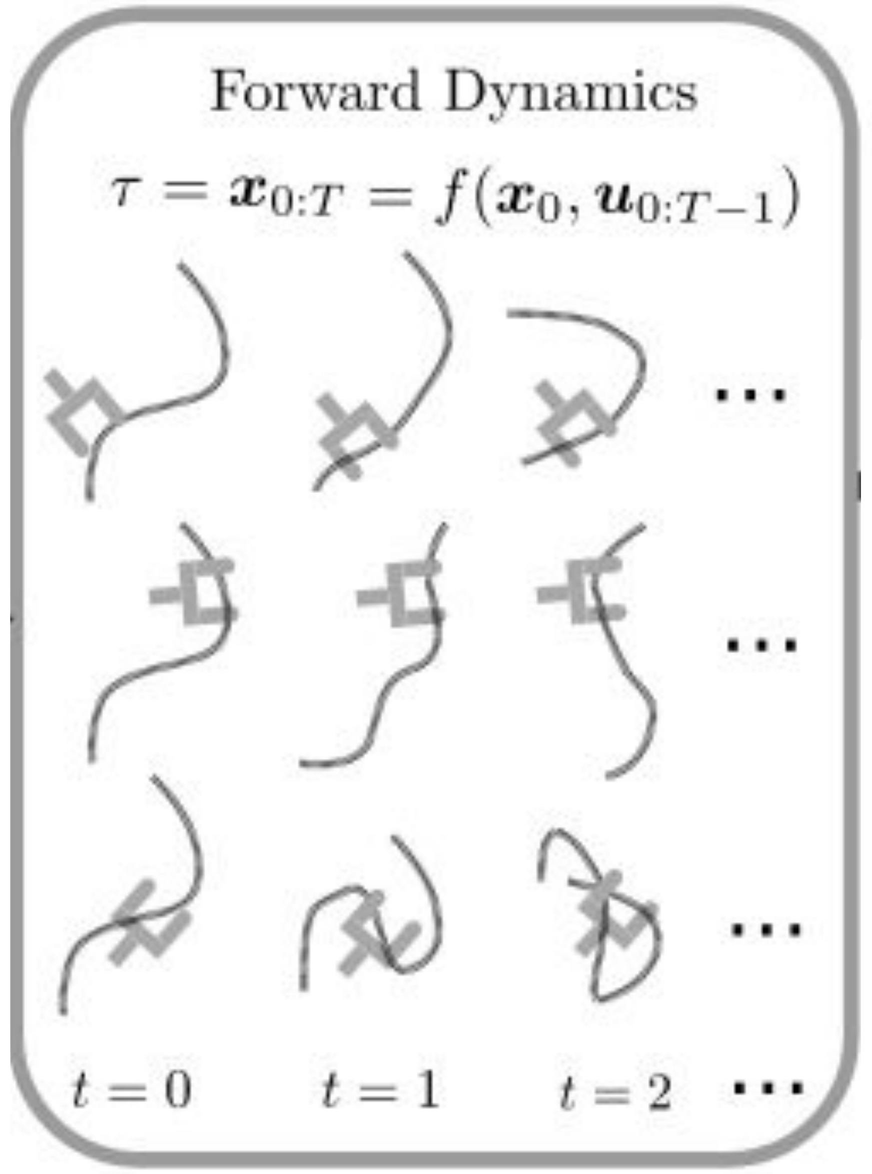
1) Analytical Method

1) Shooting in action space

Assumption: Dynamic model of the cloth is known







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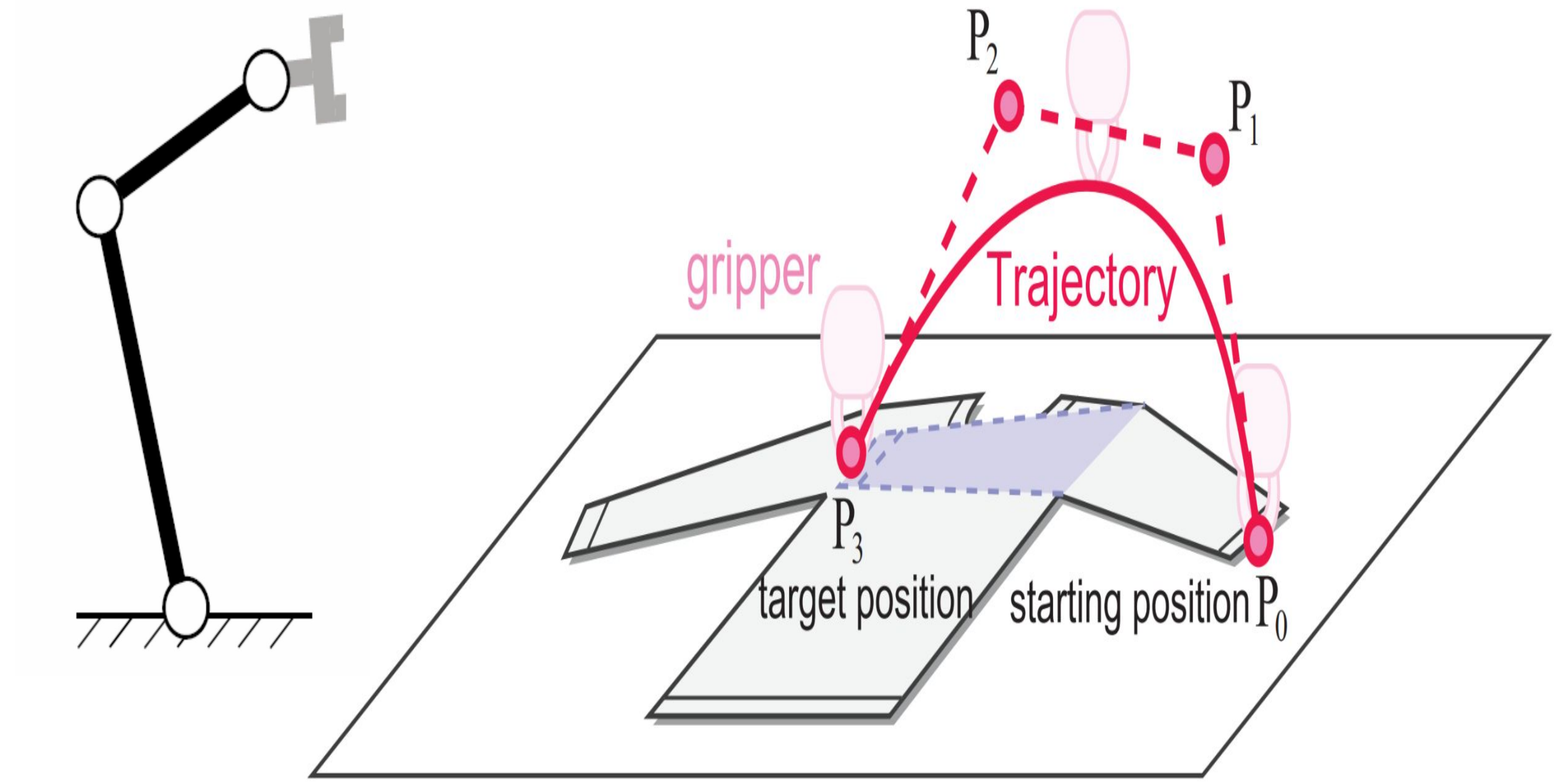
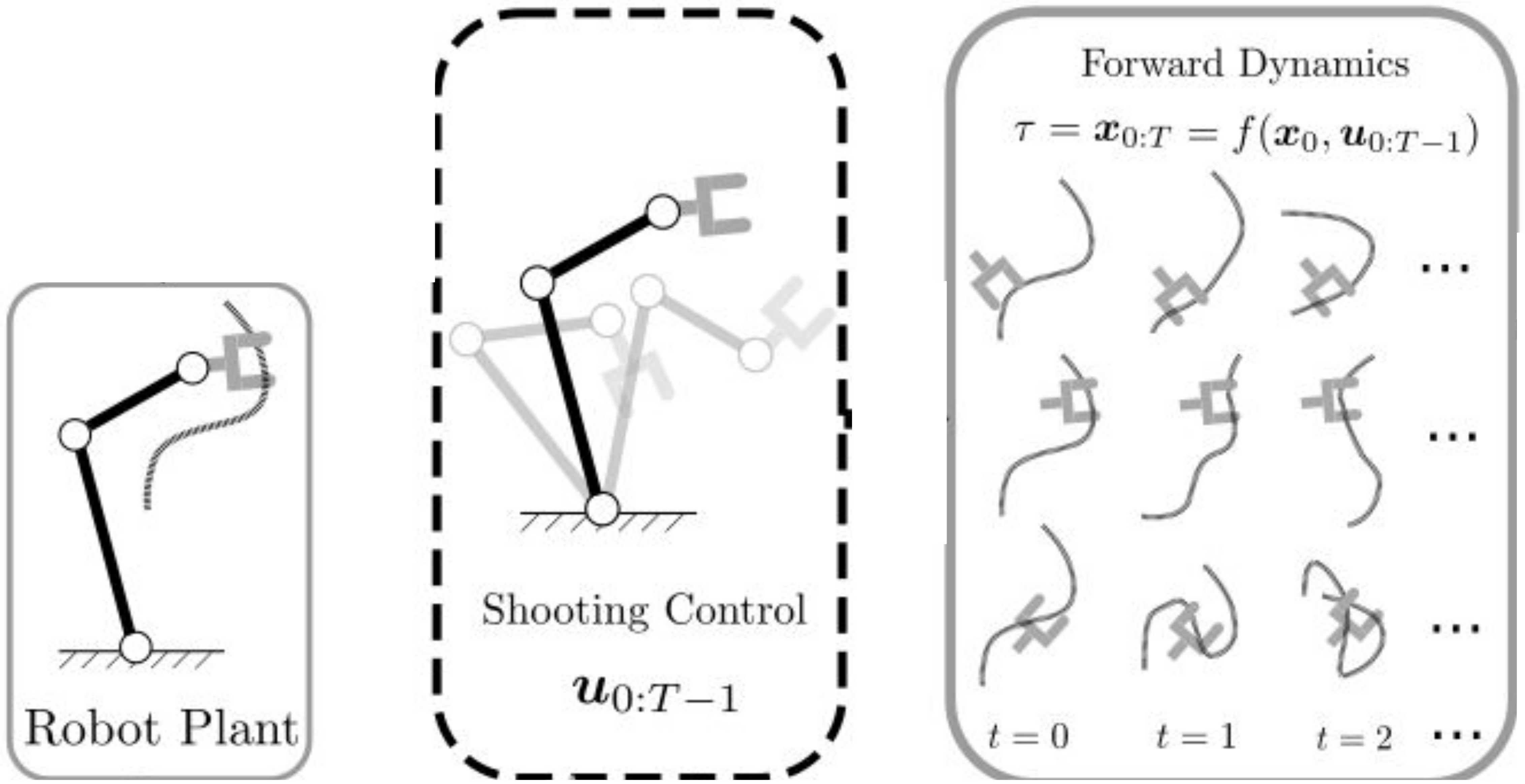
1) Shooting in action space



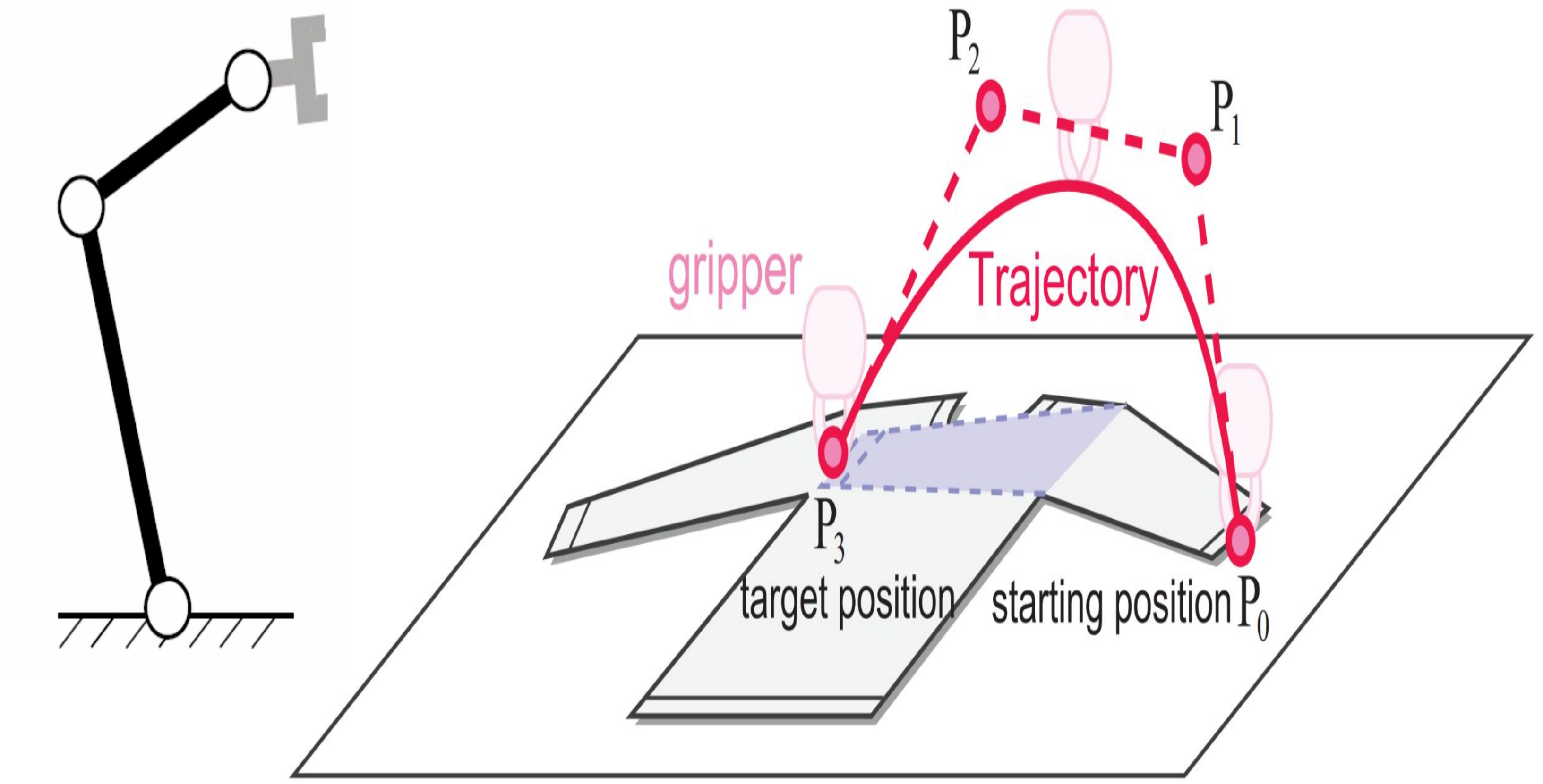
Assumption: Dynamic model of the cloth is known

Step 1) sample an action trajectory $\boldsymbol{u}_{0:T-1}$ (random/heuristic)



$u_{0:T-1}$

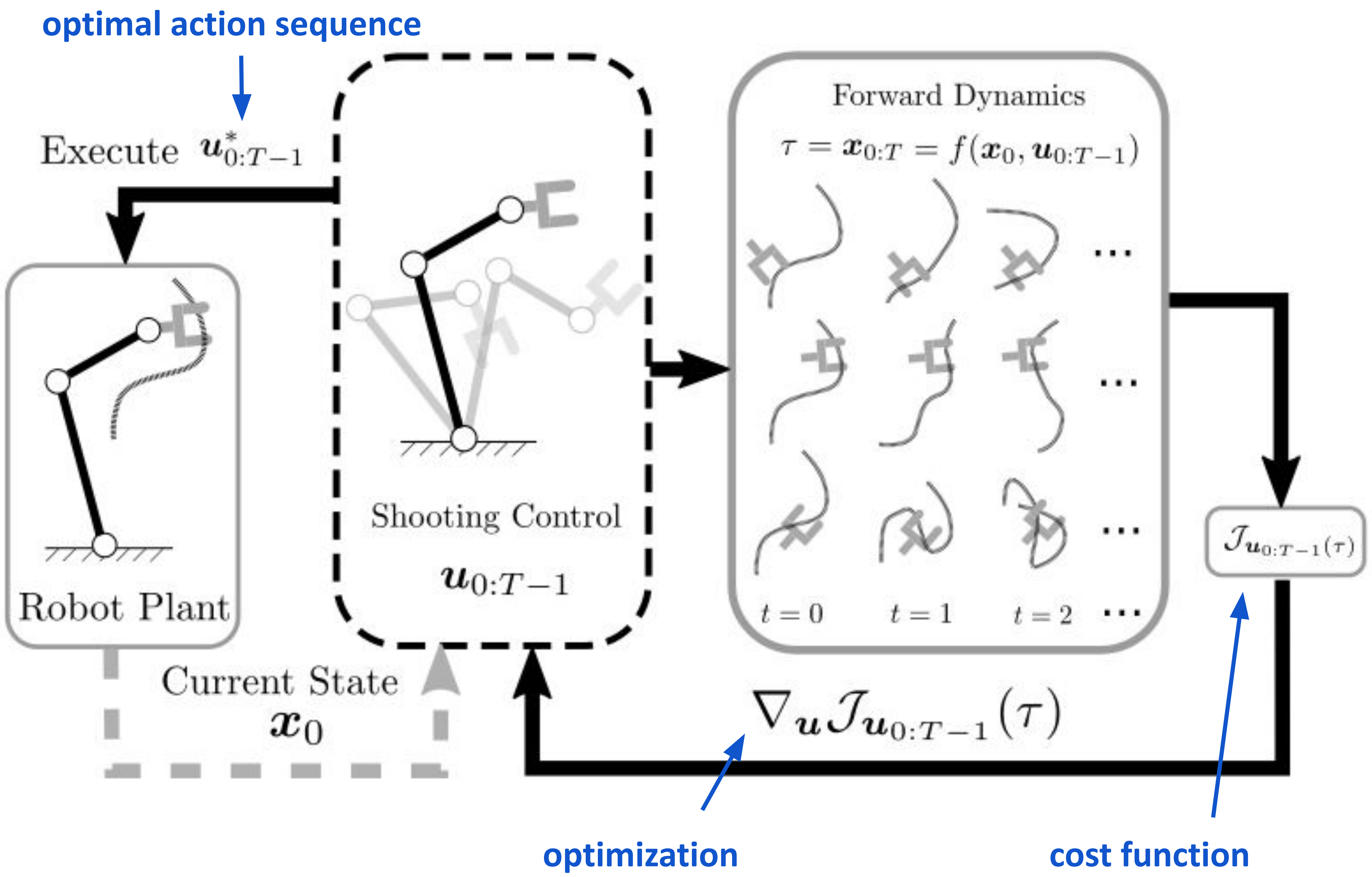
1) Shooting in action space



Assumption: Dynamic model of the cloth is known

Step 1) sample an action trajectory $\boldsymbol{u}_{0:T-1}$ (random/heuristic)

Step 2) Update actions according to evaluated costs



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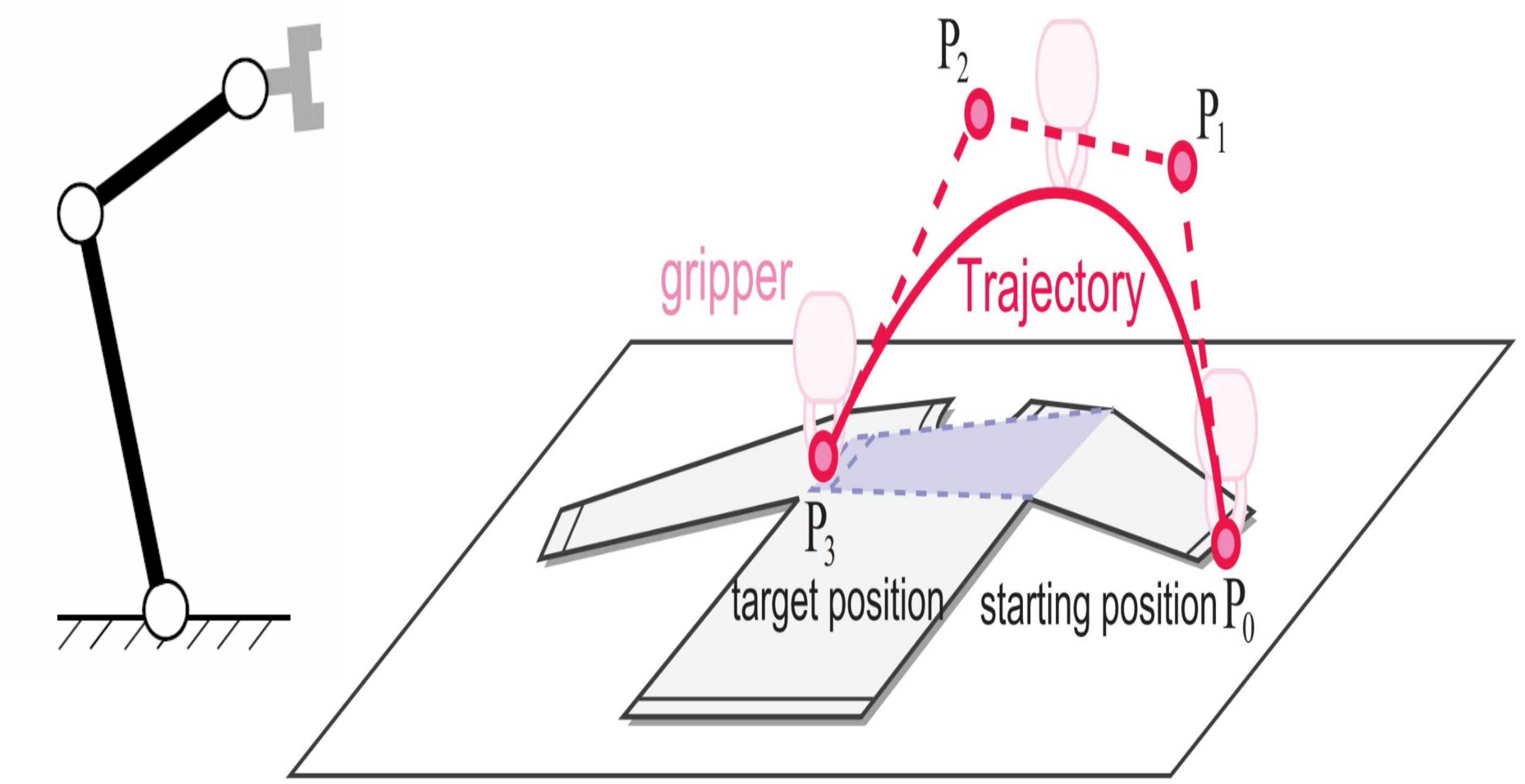
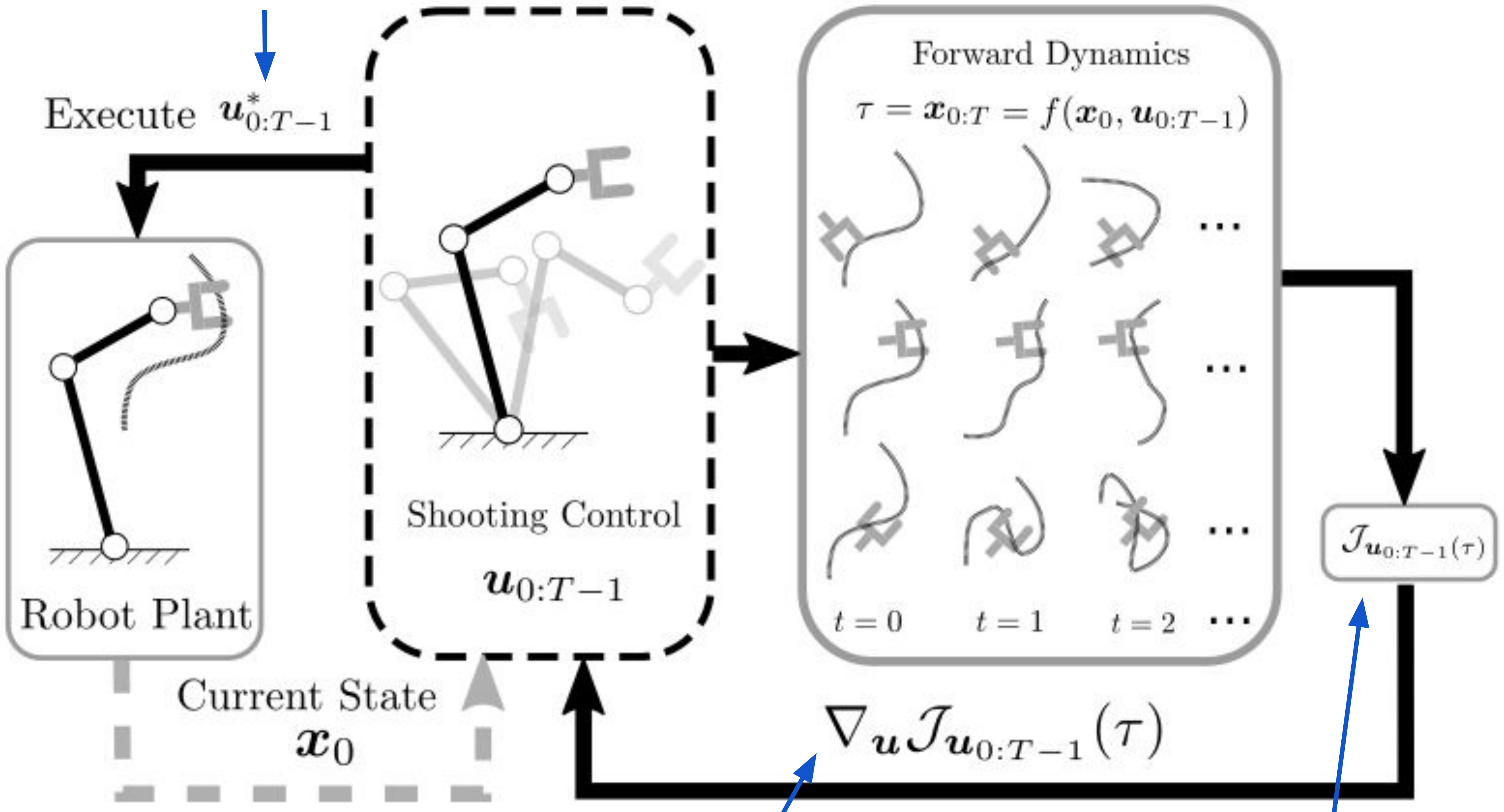


Step 1) sample an action trajectory $\boldsymbol{u}_{0:T-1}$ (random/heuristic)

Step 2) Update actions according to evaluated costs

Step 3) Resample after partial execution (receding horizon)

optimal action sequence



optimization

cost function (tedious/difficult to design!)

"Modeling, learning, perception, and control methods for deformable object manipulation.", Yin, Hang, Anastasia Varava, and Danica Kragic, Science Robotics 6.54 (2021)

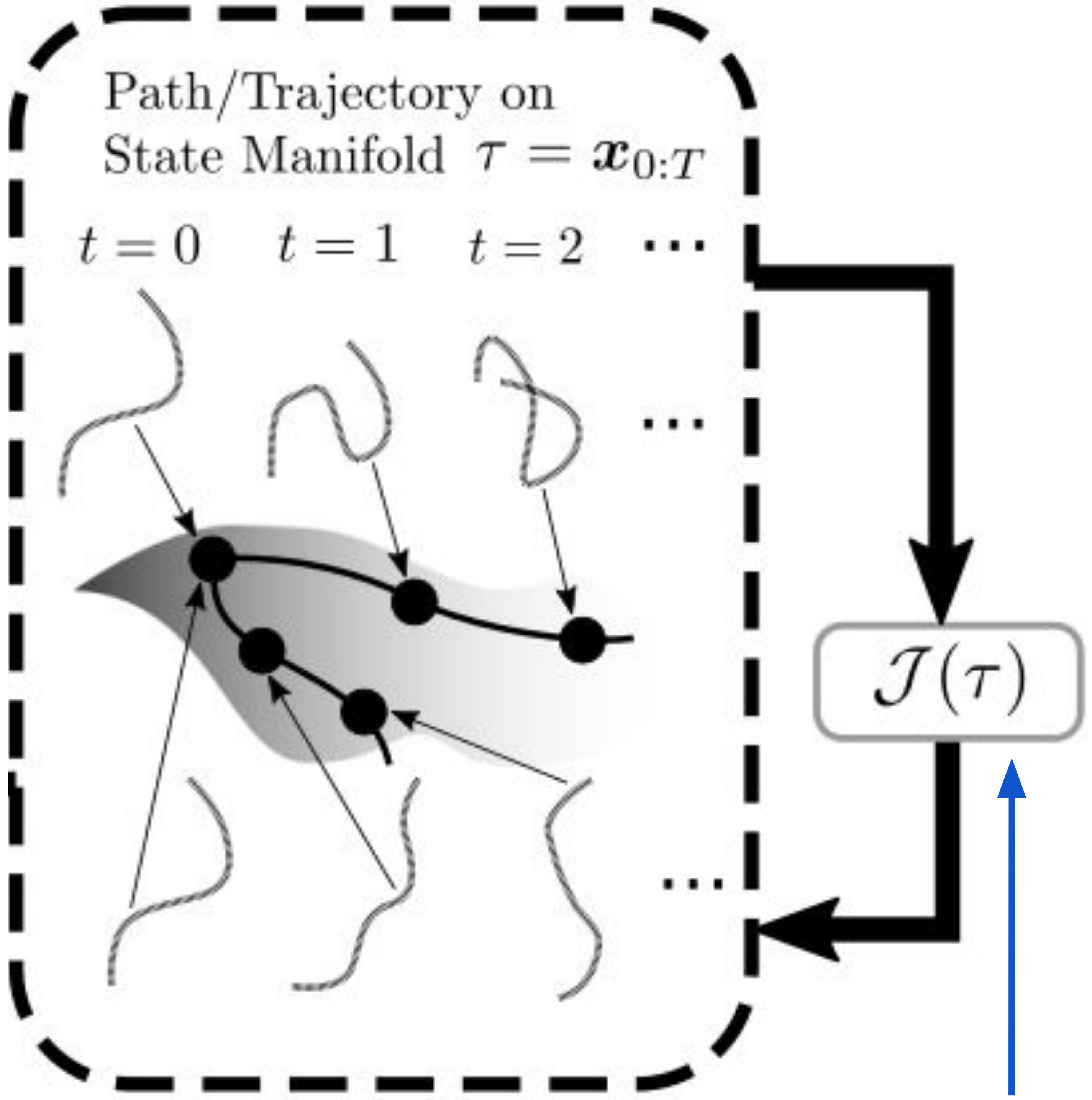
2) Search trajectories in object state space

Assumption: Dynamic model of the cloth is known

"Modeling, learning, perception, and control methods for deformable object manipulation.", Yin, Hang, Anastasia Varava, and Danica Kragic, Science Robotics 6.54 (2021)

2) Search trajectories in object state space

Step 1) find a low cost path $\tau = \boldsymbol{x}_{0:T}$ on the state manifold



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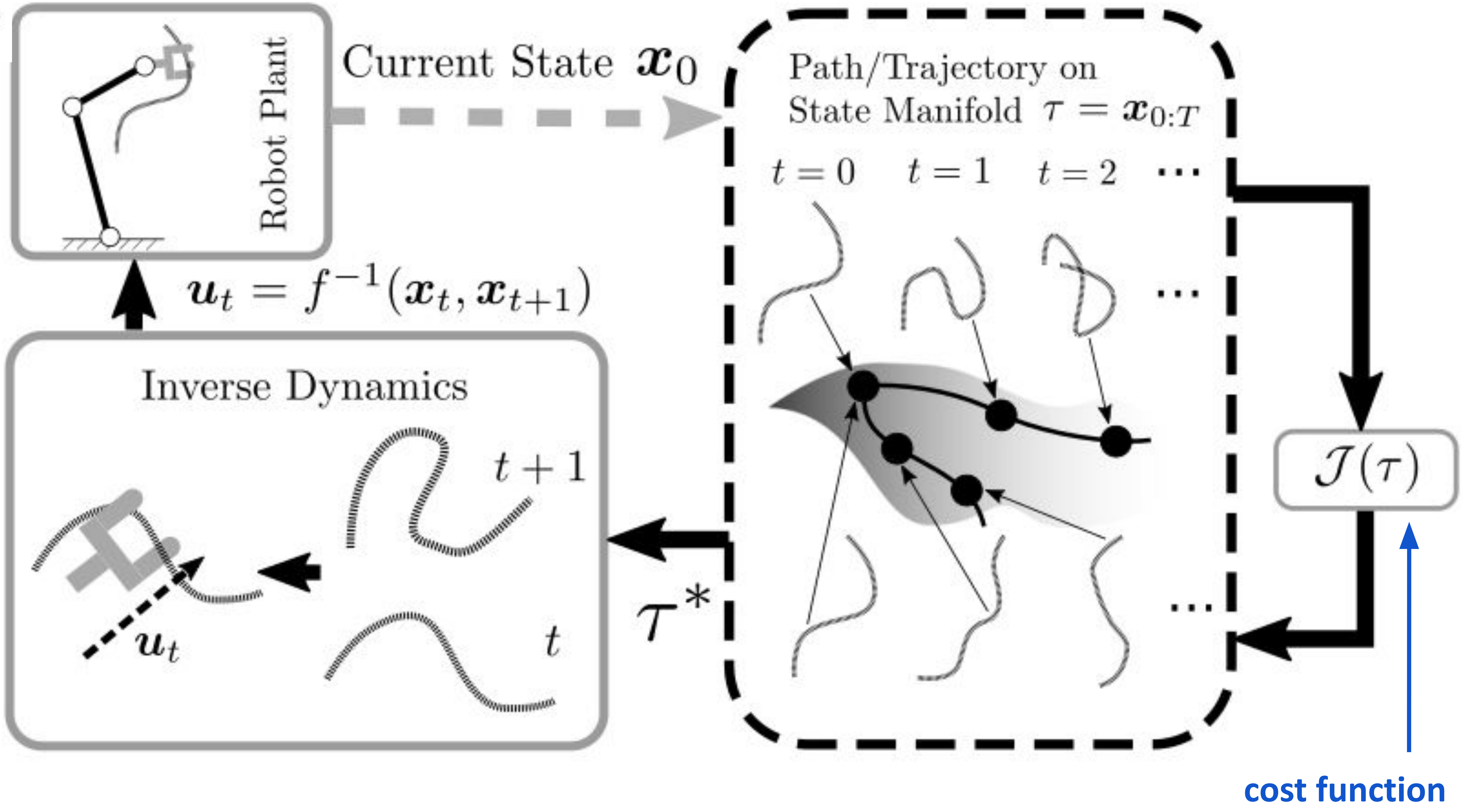
Step 1) find a low cost path $\tau = \boldsymbol{x}_{0:T}$ on the state manifold

Step 2) generate actions $\boldsymbol{u}_t$ cause transitions at each t



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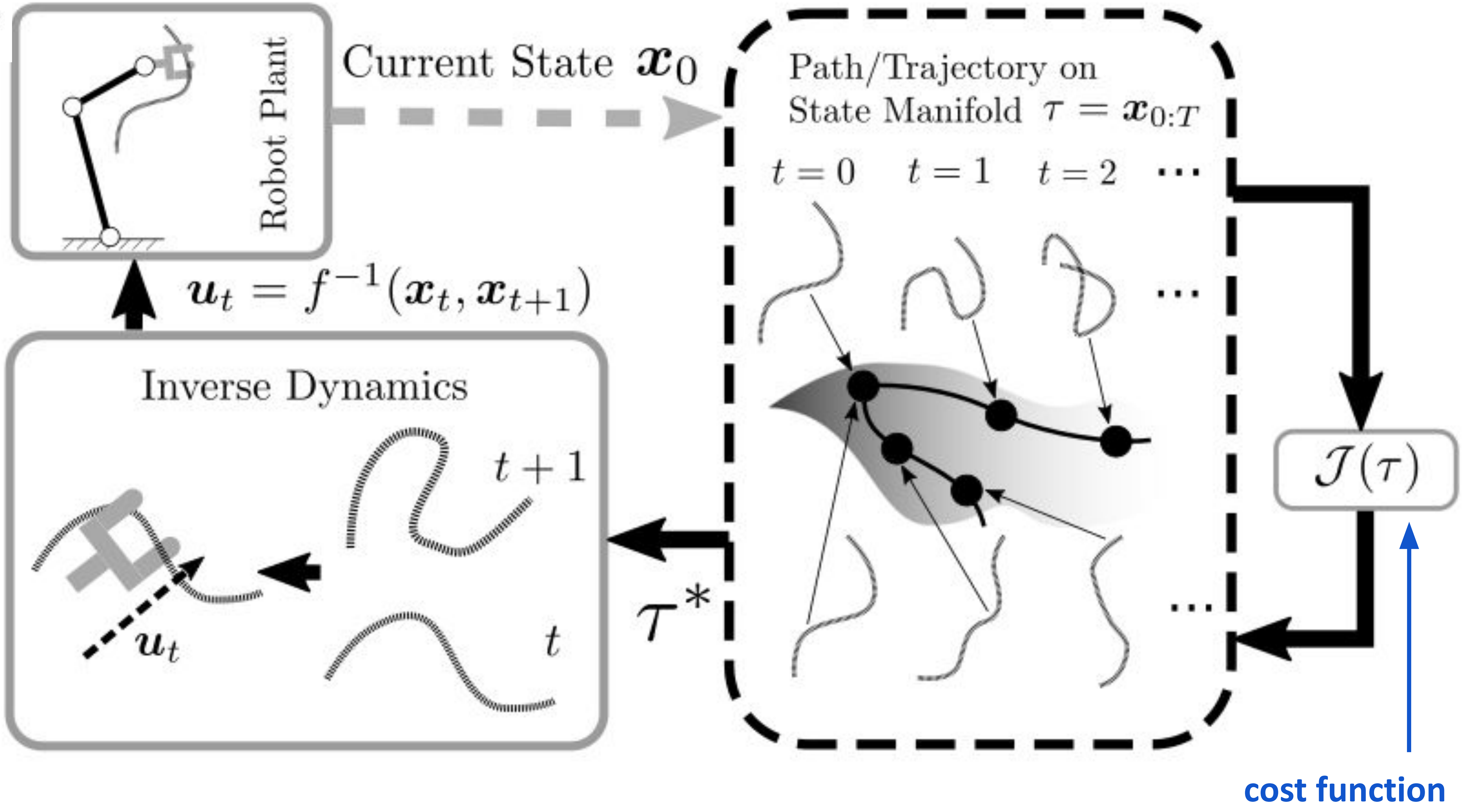
2) Search trajectories in object state space

Step 1) find a low cost path $\tau = \boldsymbol{x}_{0:T}$ on the state manifold

Step 2) generate actions $\boldsymbol{u}_t$ cause transitions at each t

Issues:
Vast search space!
Tedious to design cost function!



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In both the previous methods, we made an assumption that we already know the dynamic model

In both the previous methods, we made an assumption that we already know the dynamic model

But in reality, it is very difficult to find the dynamic model of the cloth due to

- high dimensionality
- nonlinear dynamics
- self collision

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Can I solve this task without explicitly having a dynamic model?

Can I solve this task without explicitly having a dynamic model?

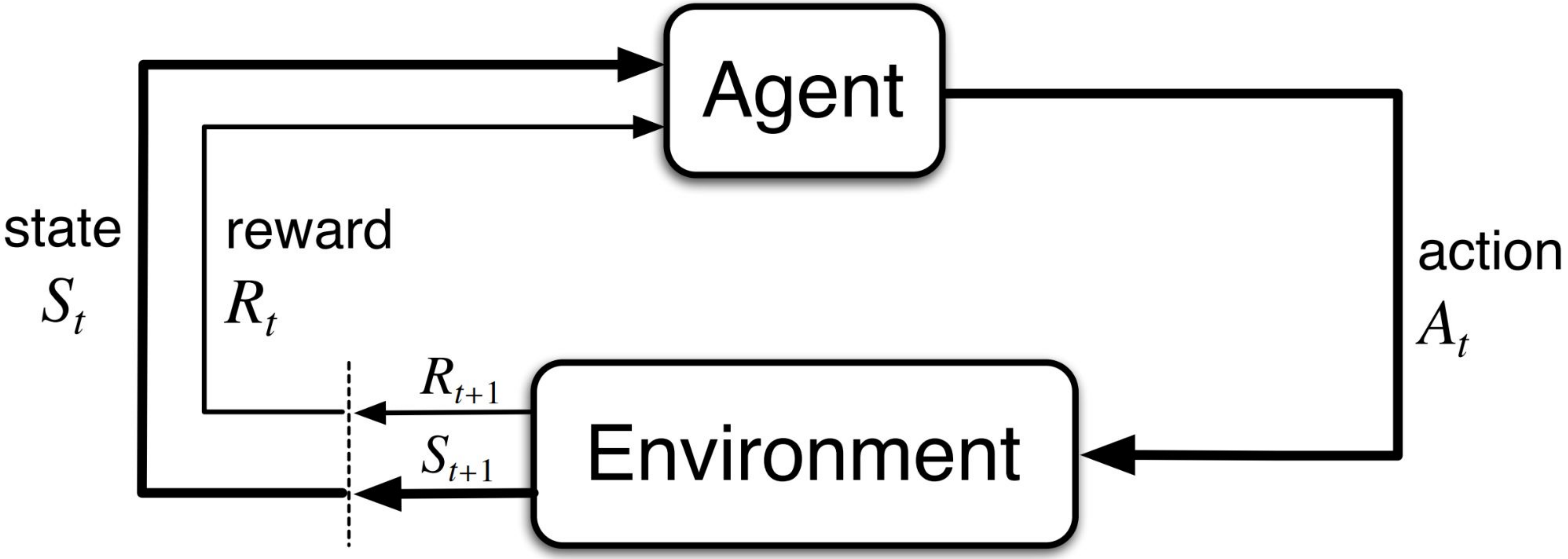
Can I learn to control in an end to end manner?

Can I solve this task without explicitly having a dynamic model?

Can I learn to control in an end to end manner?

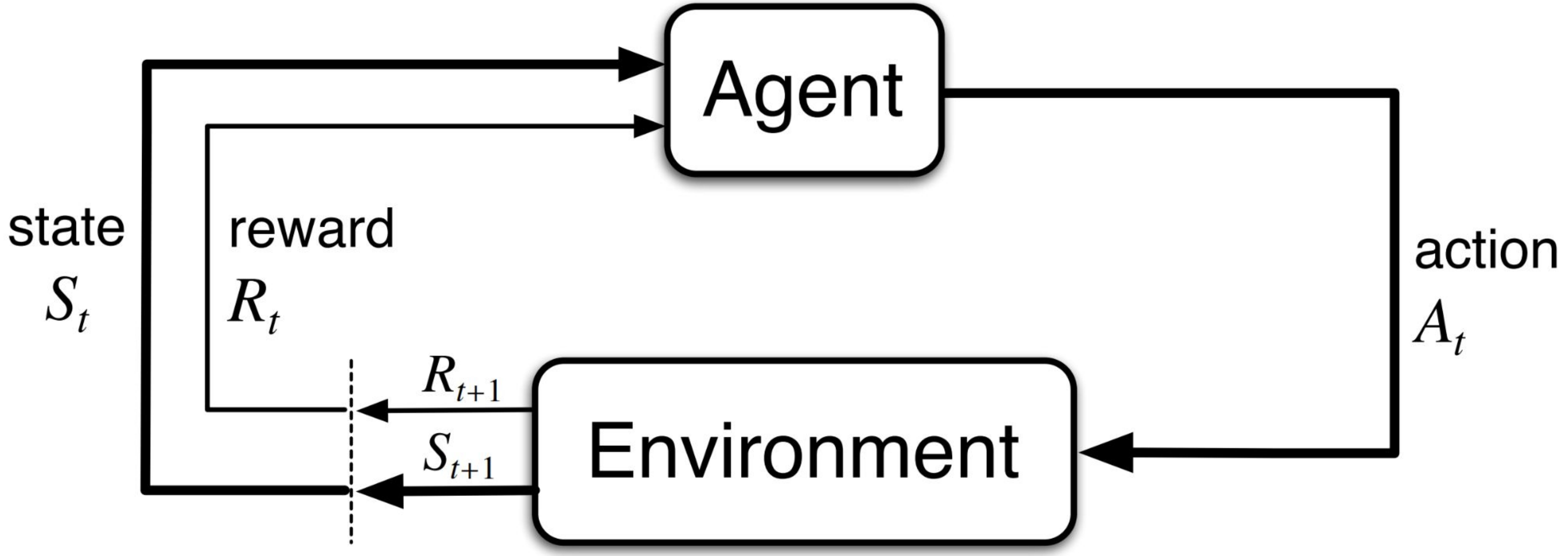
Model free learning based approaches!

Reinforcement Learning

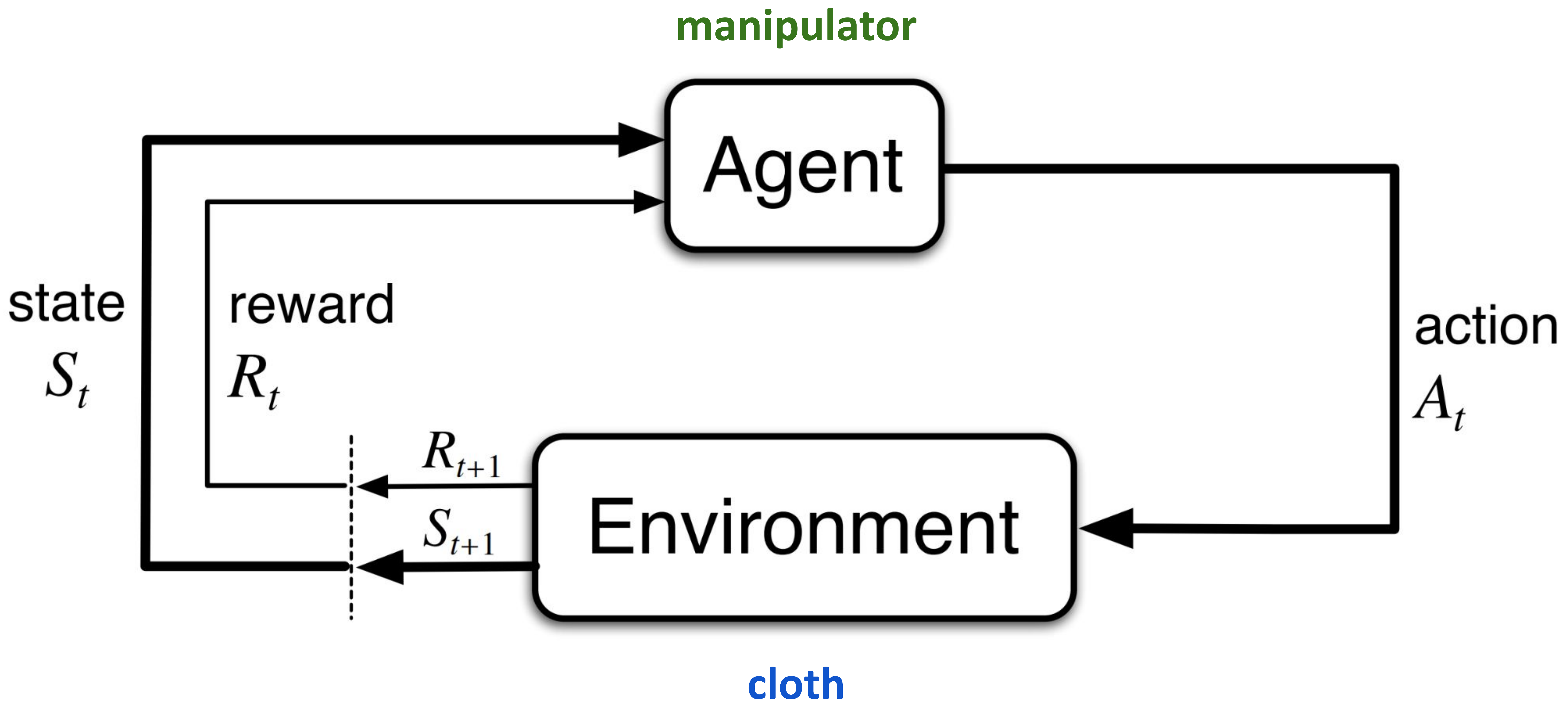


Reinforcement Learning

manipulator

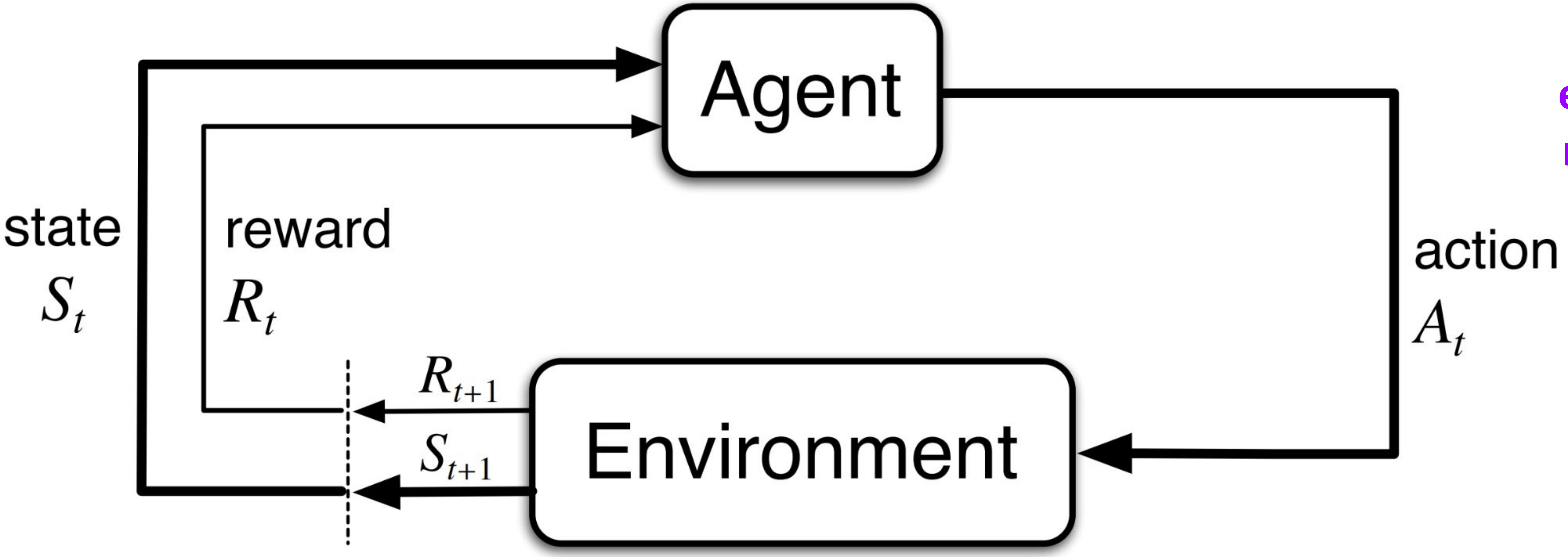


Reinforcement Learning



Reinforcement Learning

manipulator



cloth

end effector movements

- position
- velocity
- effort

manipulation primitives

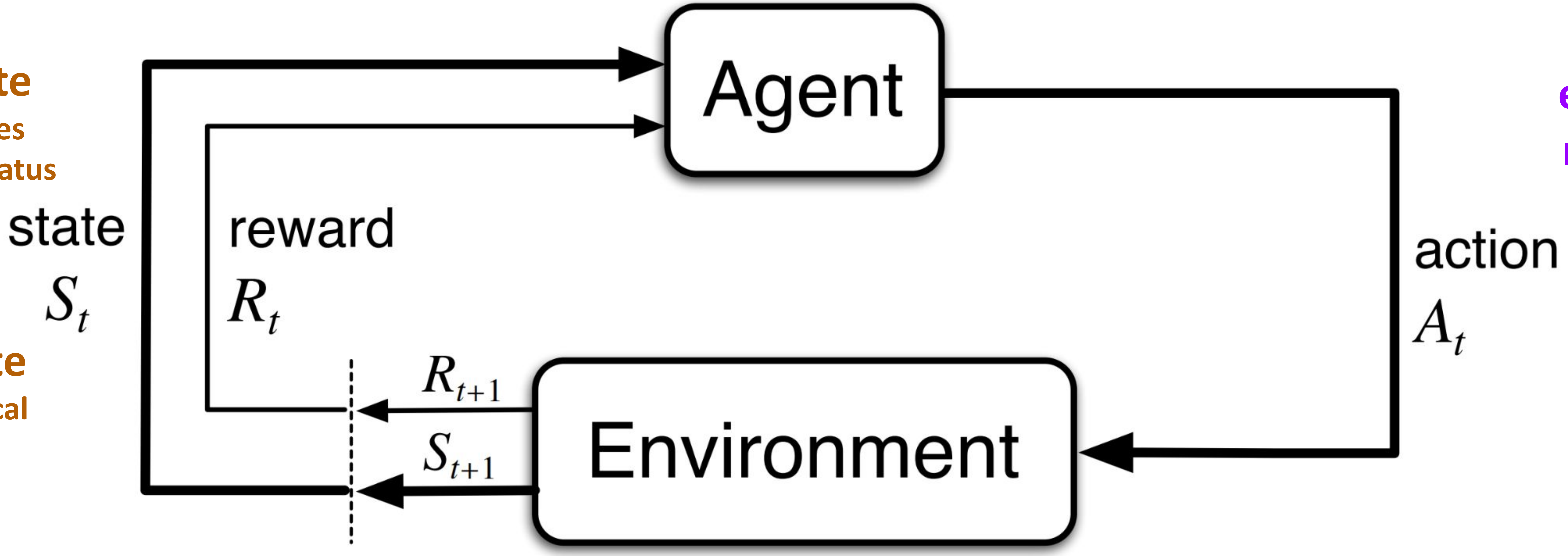
- grasp
- push
- pull
- stretch
- pinch
- fling!

Reinforcement Learning

manipulator

robot state
- joint angles
- gripper status

cloth state
- topological
- spherical

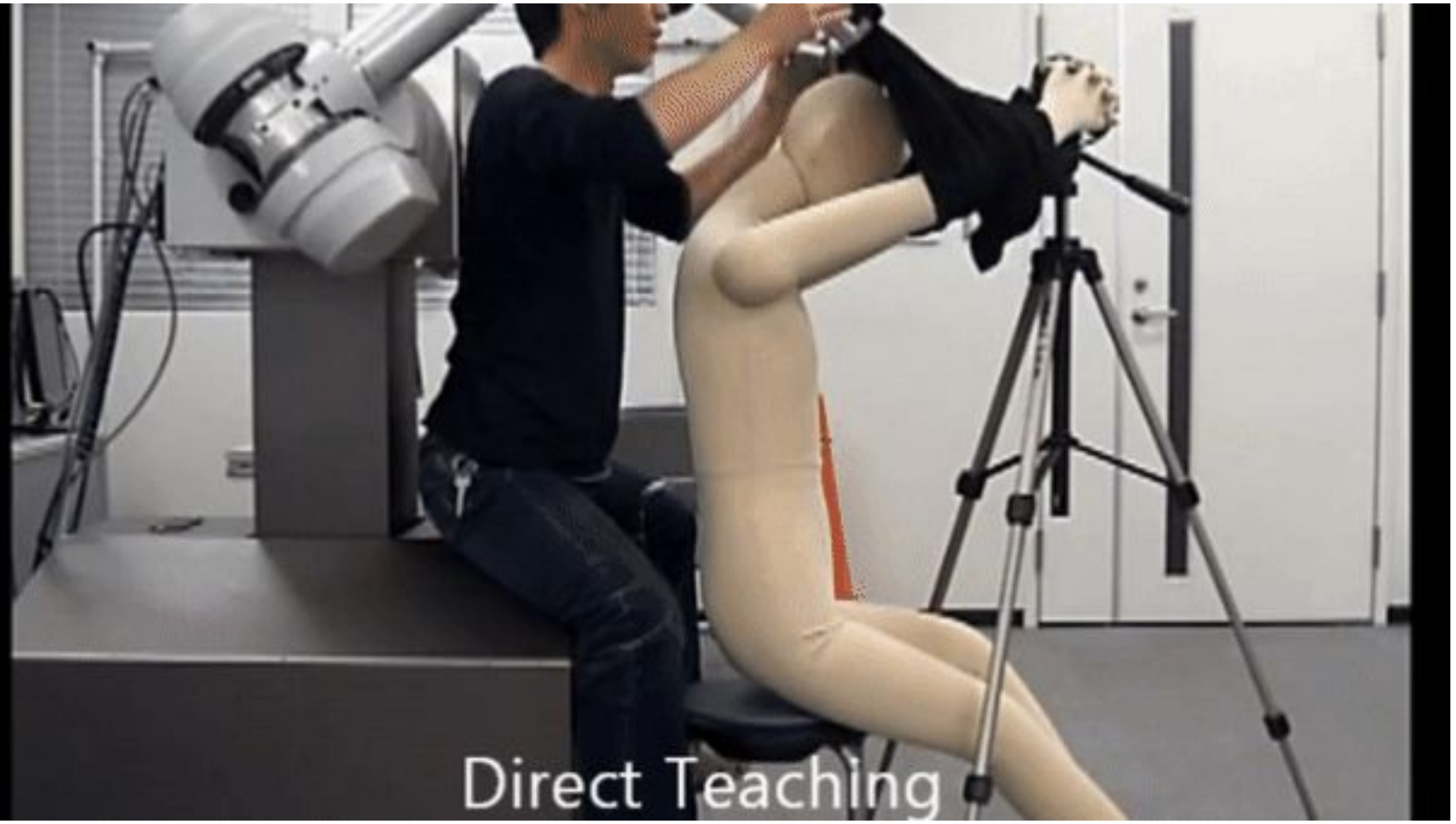


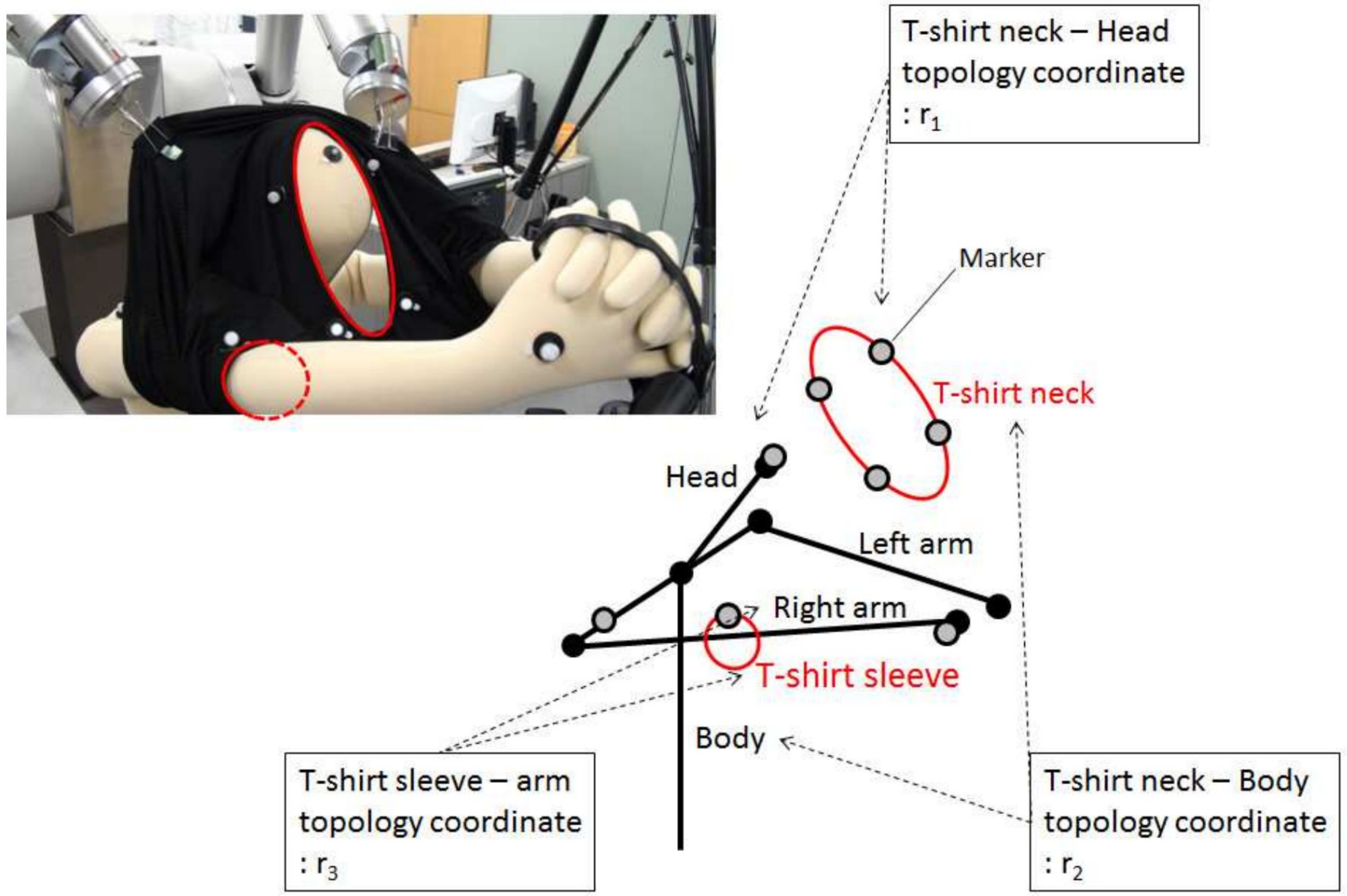
cloth

end effector movements
- position
- velocity
- effort

manipulation primitives
- grasp
- push
- pull
- stretch
- pinch
- fling!

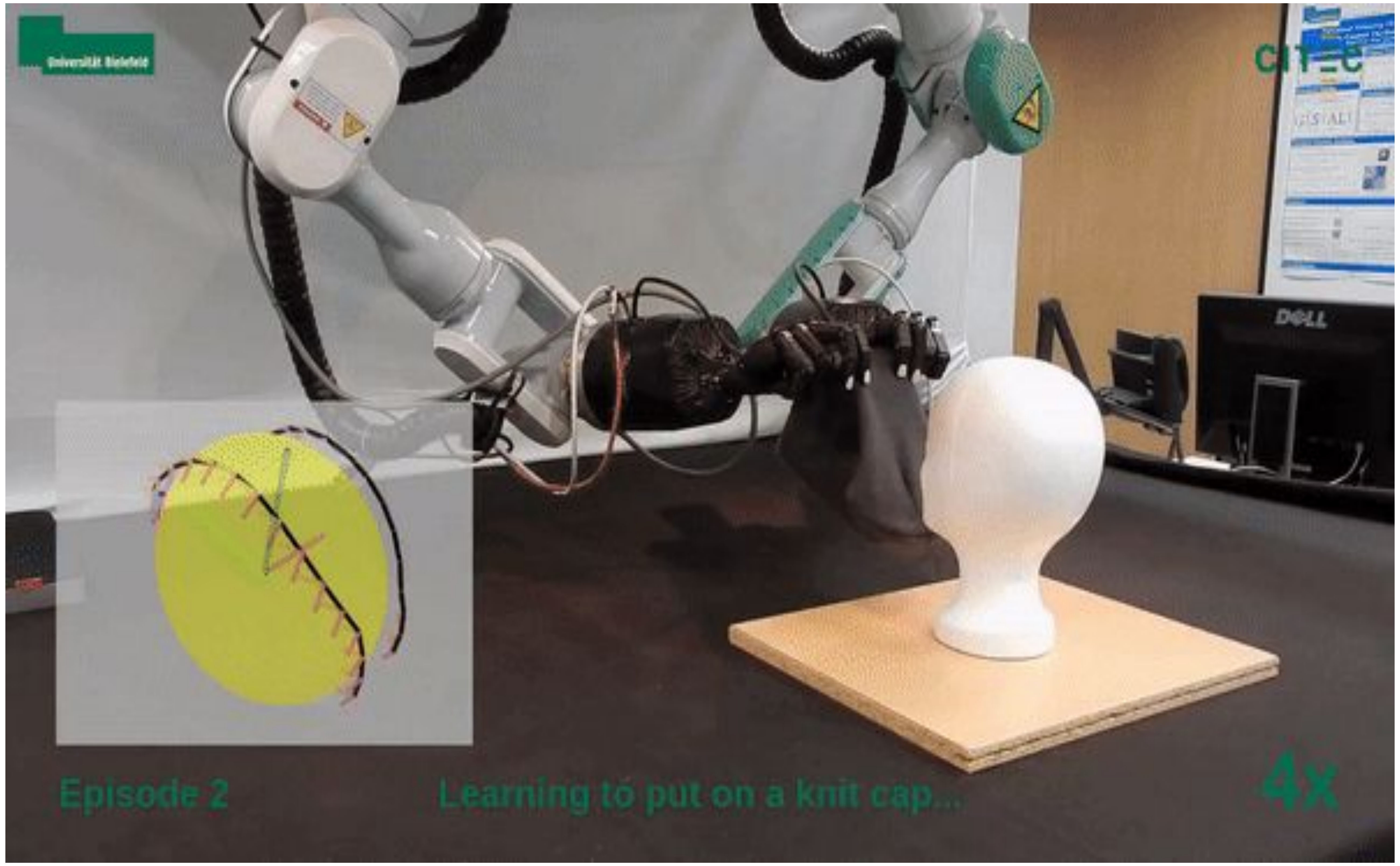
Example: Topological coordinates





Tamei, T., Matsubara, T., Rai, A., & Shibata, T. (2011). Reinforcement learning of clothing assistance with a dual-arm robot. 2011 11th IEEE-RAS International Conference on Humanoid Robots, 733–738. doi:10.1109/Humanoids.2011.6100915

Example: Spherical coordinates



Twardon, L., & Ritter, H. (2018). Learning to Put On a Knit Cap in a Head-Centric Policy Space. IEEE Robotics and Automation Letters, 3(2), 764–771. doi:10.1109/LRA.2018.2792153

Objective

"learn an action policy that maximizes cumulative reward G_t over time"

$$G_t = R_{t+1} + R_{t+2} + R_{t+3} + \cdots = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1}$$

discount factor ($0<\gamma<1$)

"immediate rewards have more importance than future rewards"

RL can be computationally expensive and time consuming!

credits: x.com/Sentdex

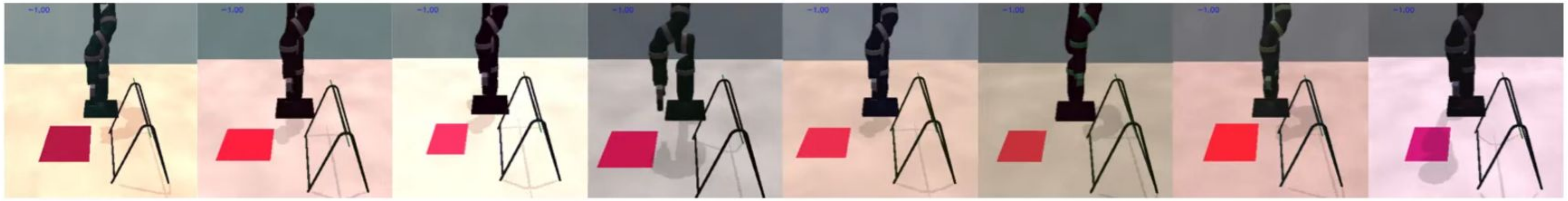
But can I get the data from simulators and use my learned method in real world?

But can I get the data from simulators and use my learned method in real world?

sim2real

Sim-to-Real Reinforcement Learning for Deformable Object Manipulation

Jan Matas, Stephen James, Andrew J. Davidson
Department of Computing
Imperial College London



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Contributions

For deformable objects,

- learn manipulation policies through a combination of SOTA DRL algorithms

- learn policies in simulations that can be transferred to real world *without* additional training

Sim-to-Real Reinforcement Learning for Deformable Object Manipulation

Jan Matas
Department of Computing
Imperial College London
jm6214@imperial.ac.uk

Stephen James
Department of Computing
Imperial College London
slj12@imperial.ac.uk

Andrew J. Davison
Department of Computing
Imperial College London
a.davison@imperial.ac.uk

Abstract: We have seen much recent progress in rigid object manipulation, but interaction with deformable objects has notably lagged behind. Due to the large configuration space of deformable objects, solutions using traditional modelling approaches require significant engineering work. Perhaps then, bypassing the need for explicit modelling and instead learning the control in an end-to-end manner serves as a better approach? Despite the growing interest in the use of end-to-end robot learning approaches, only a small amount of work has focused on their applicability to deformable object manipulation. Moreover, due to the large amount of data needed to learn these end-to-end solutions, an emerging trend is to learn control policies in simulation and then transfer them over to the real world. To-date, no work has explored whether it is possible to learn and transfer deformable object policies. We believe that if sim-to-real methods are to be employed further, then it should be possible to learn to interact with a wide variety of objects, and not only rigid objects. In this work, we use a combination of state-of-the-art deep reinforcement learning algorithms to solve the problem of manipulating deformable objects (specifically cloth). We evaluate our approach on three tasks — folding a towel up to a mark, folding a face towel diagonally, and draping a piece of cloth over a hanger. Our agents are fully trained in simulation with domain randomisation, and then successfully deployed in the real world without having seen any real deformable objects.

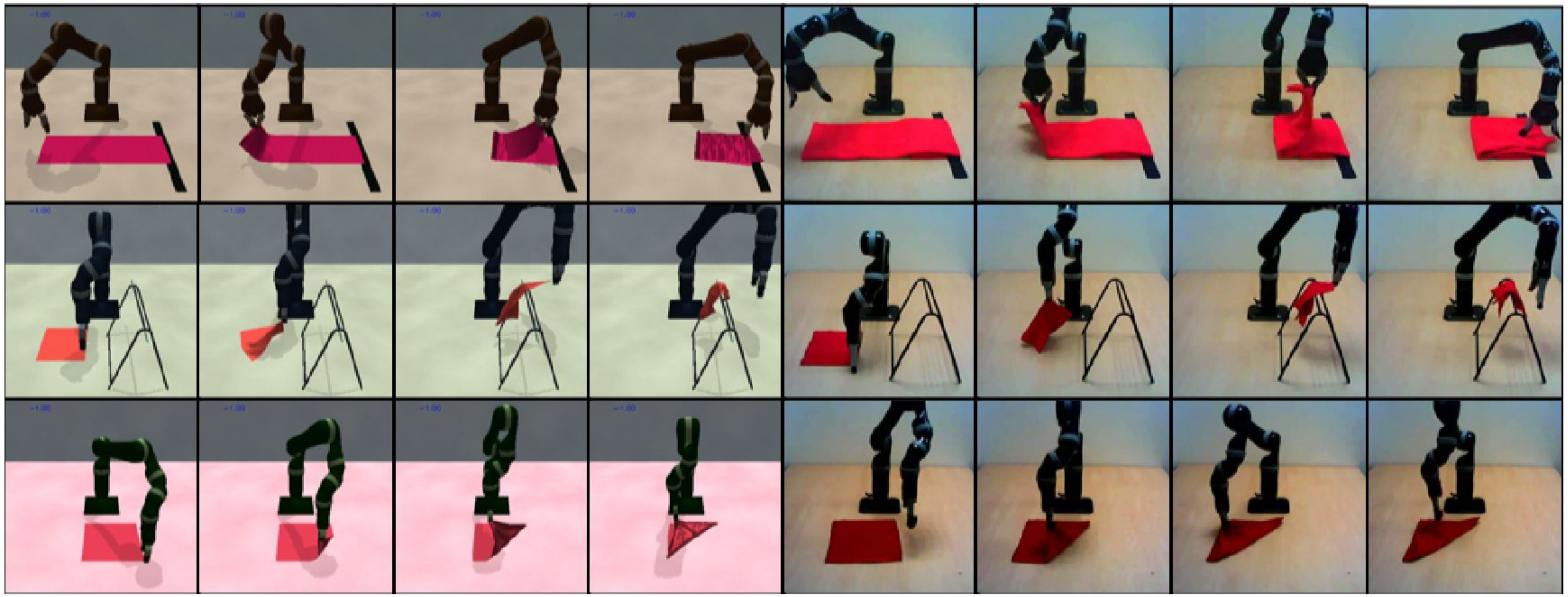
Tamei, T., Matsubara, T., Rai, A., & Shibata, T. (2011). Reinforcement learning of clothing assistance with a dual-arm robot. 2011 11th IEEE-RAS International Conference on Humanoid Robots, 733–738. doi:10.1109/Humanoids.2011.6100915

Tasks

Fold until the tape

Hang towel on hanger

Diagonal cloth fold



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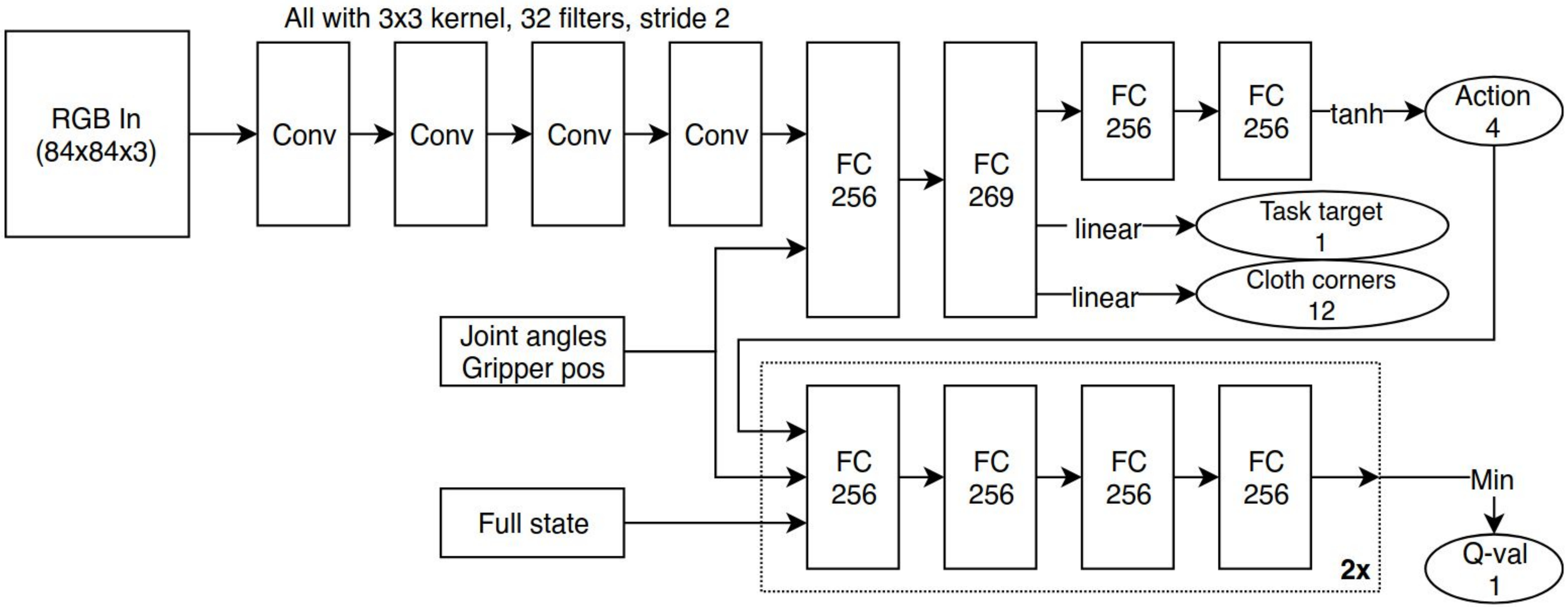
Network Architecture



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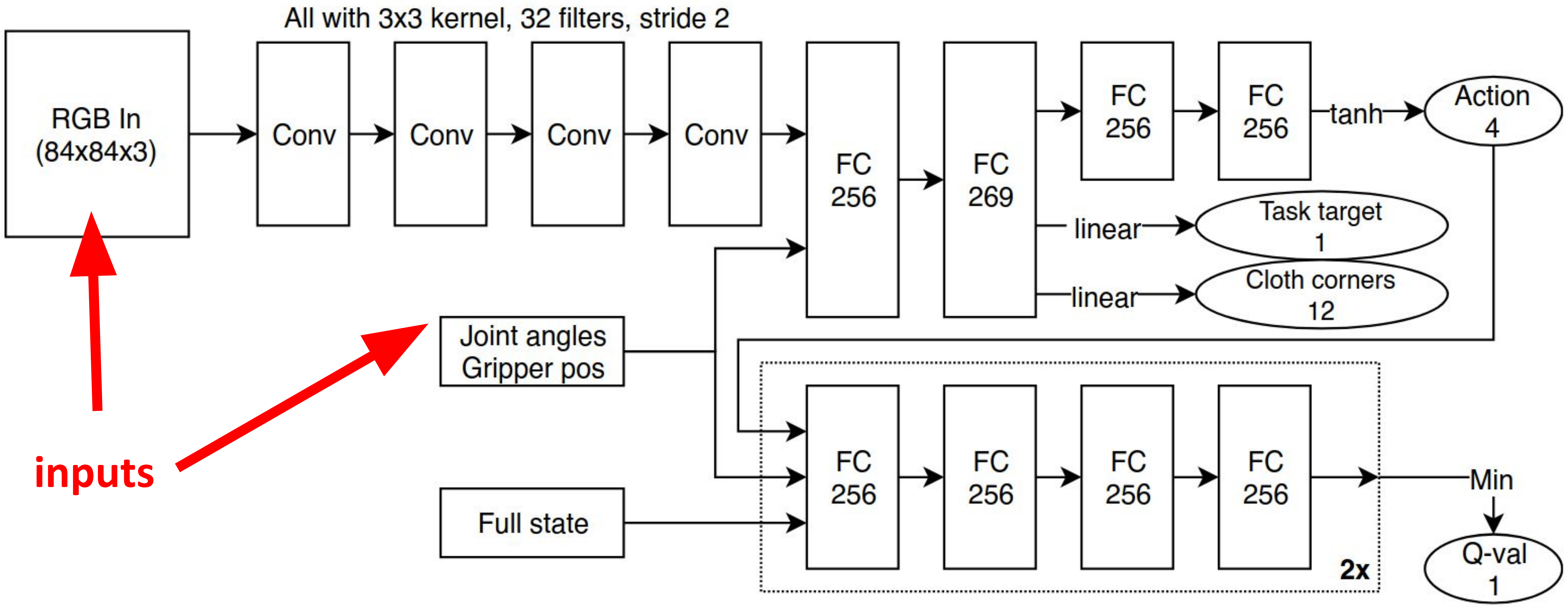

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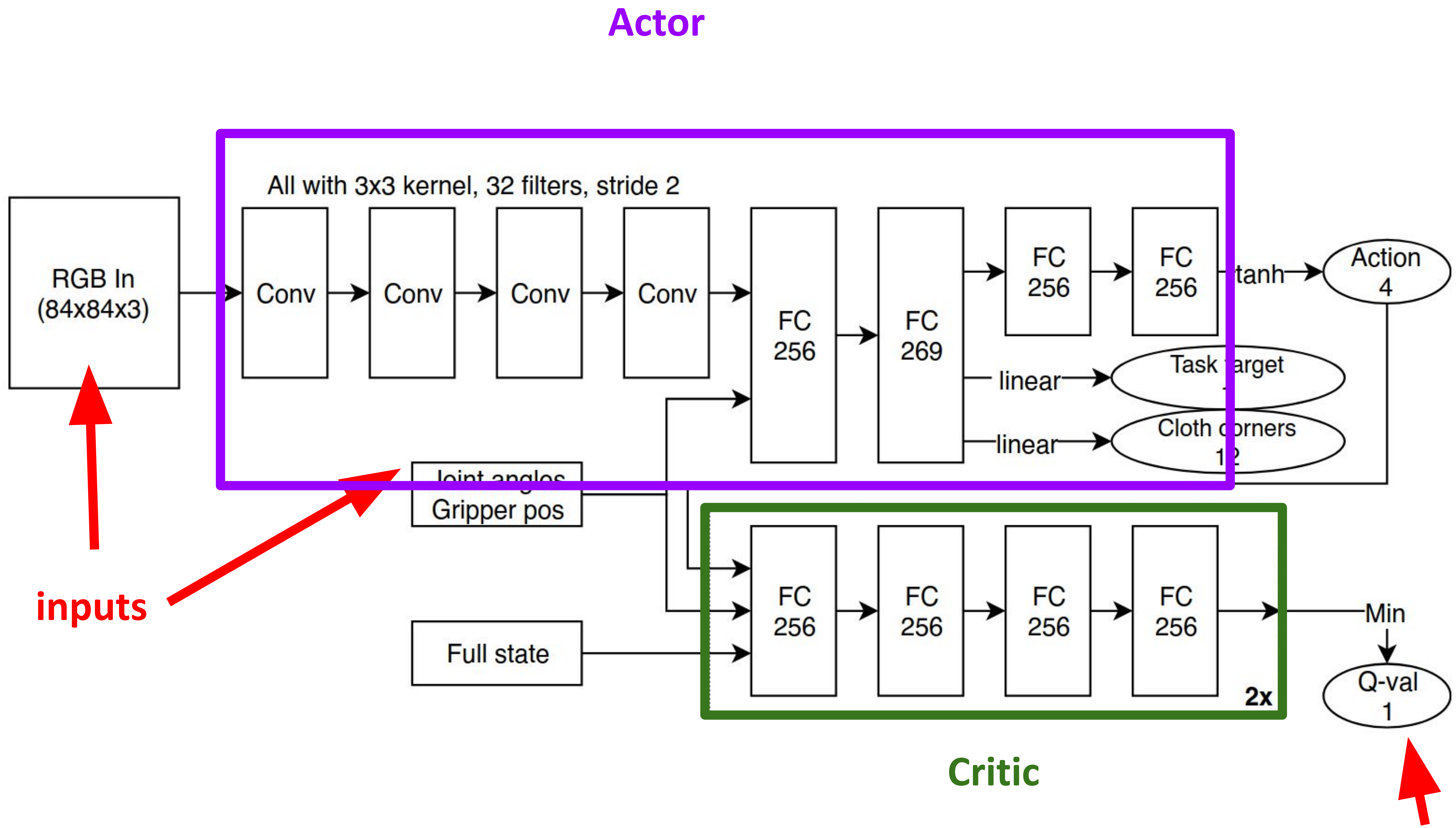

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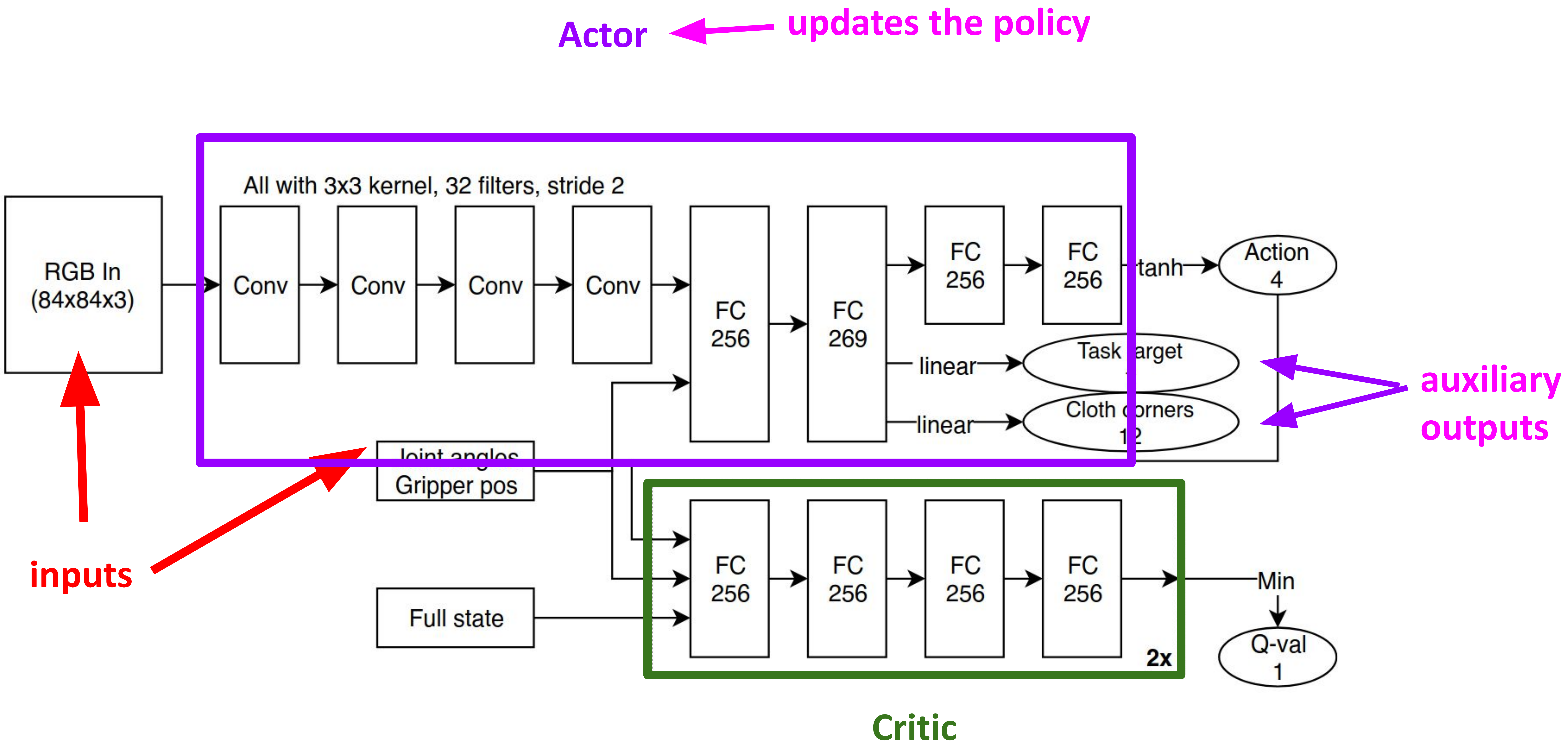

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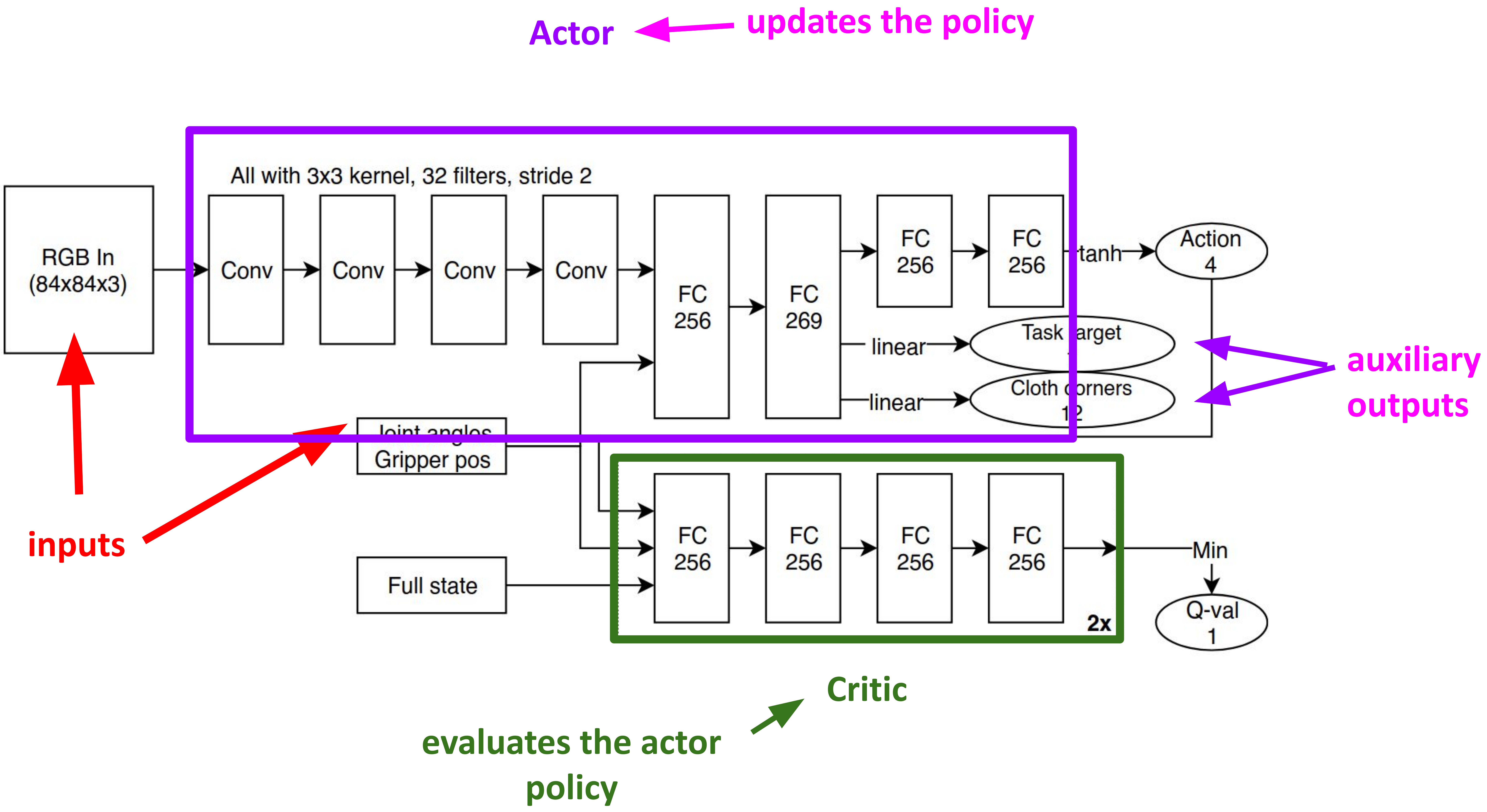

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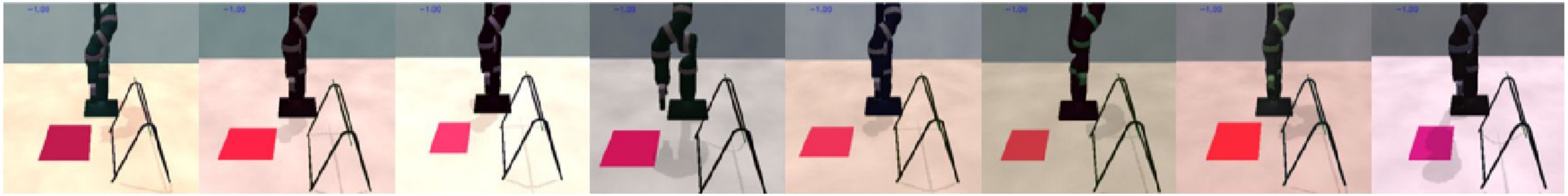
Domain Randomization



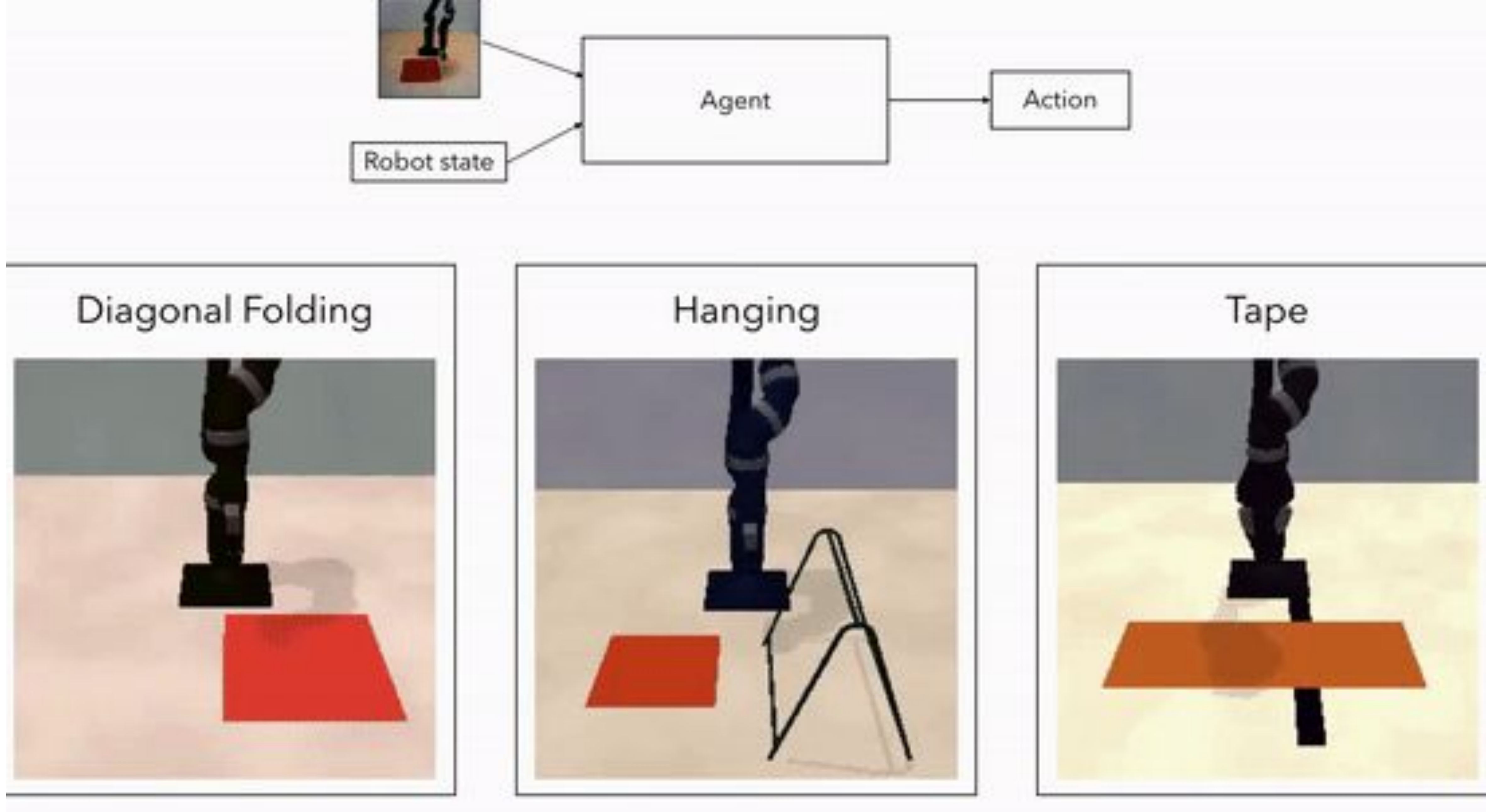
randomized attributes:

- table textures
- cloth and arm colours
- light position
- camera position and orientation,
- cloth size and position,
- hanger size and position,
- initial arm position and size of arm base

Tamei, T., Matsubara, T., Rai, A., & Shibata, T. (2011). Reinforcement learning of clothing assistance with a dual-arm robot. 2011 11th IEEE-RAS International Conference on Humanoid Robots, 733–738. doi:10.1109/Humanoids.2011.6100915

DR

sim



real

Policy trained in simulation transfers to real world **without further training**

Tamei, T., Matsubara, T., Rai, A., & Shibata, T. (2011). Reinforcement learning of clothing assistance with a dual-arm robot. 2011 11th IEEE-RAS International Conference on Humanoid Robots, 733–738. doi:10.1109/Humanoids.2011.6100915

Results

Simulations

Success rates (Sim)	
Diagonal folding	90%
Hanging	77%
Tape	86%

Real world

Hanging task	
Vicinity	100%
Grasp	76.6%
Drape over	70%
Full success	46.6%

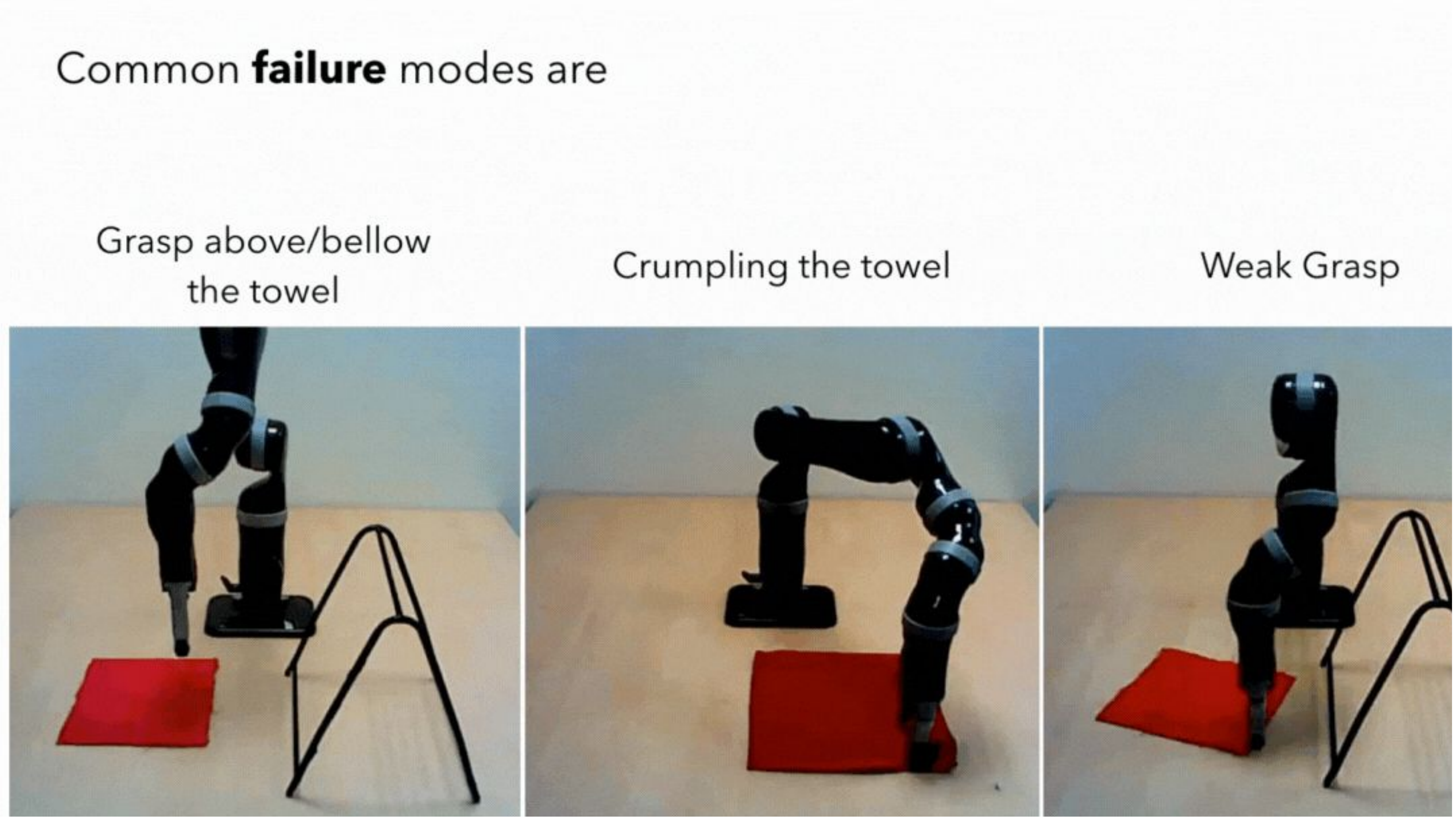
Diagonal folding task	
Grasp	66.6%
Not crumpled	66.6%
$d \leq 0.15m$	53.3%
$d \leq 0.1m$	40%
$d \leq 0.05m$	20%

Tape folding task	
Grasp	90%
$d \leq 0.15m$	90%
$d \leq 0.1m$	76.6%
$d \leq 0.05m$	43%

vicinity: gripper being from 5 cm from the cloth
drape over: cloth touching top part of the hanger
full success: cloth does not fall after released
not crumpled: adjacent corners are more than 15 cms from each other
d: distance between the diagonal (folded) corners (lower the better)

Tamei, T., Matsubara, T., Rai, A., & Shibata, T. (2011). Reinforcement learning of clothing assistance with a dual-arm robot. 2011 11th IEEE-RAS International Conference on Humanoid Robots, 733–738. doi:10.1109/Humanoids.2011.6100915

Failure Modes



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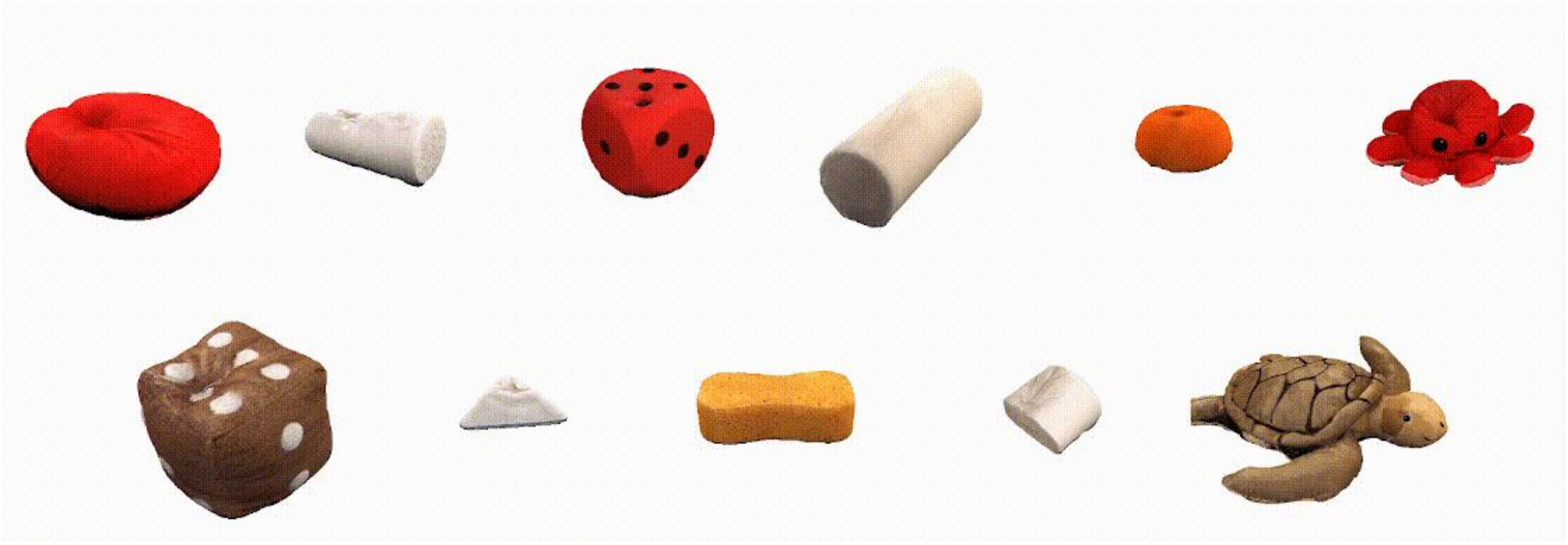
Open Problems

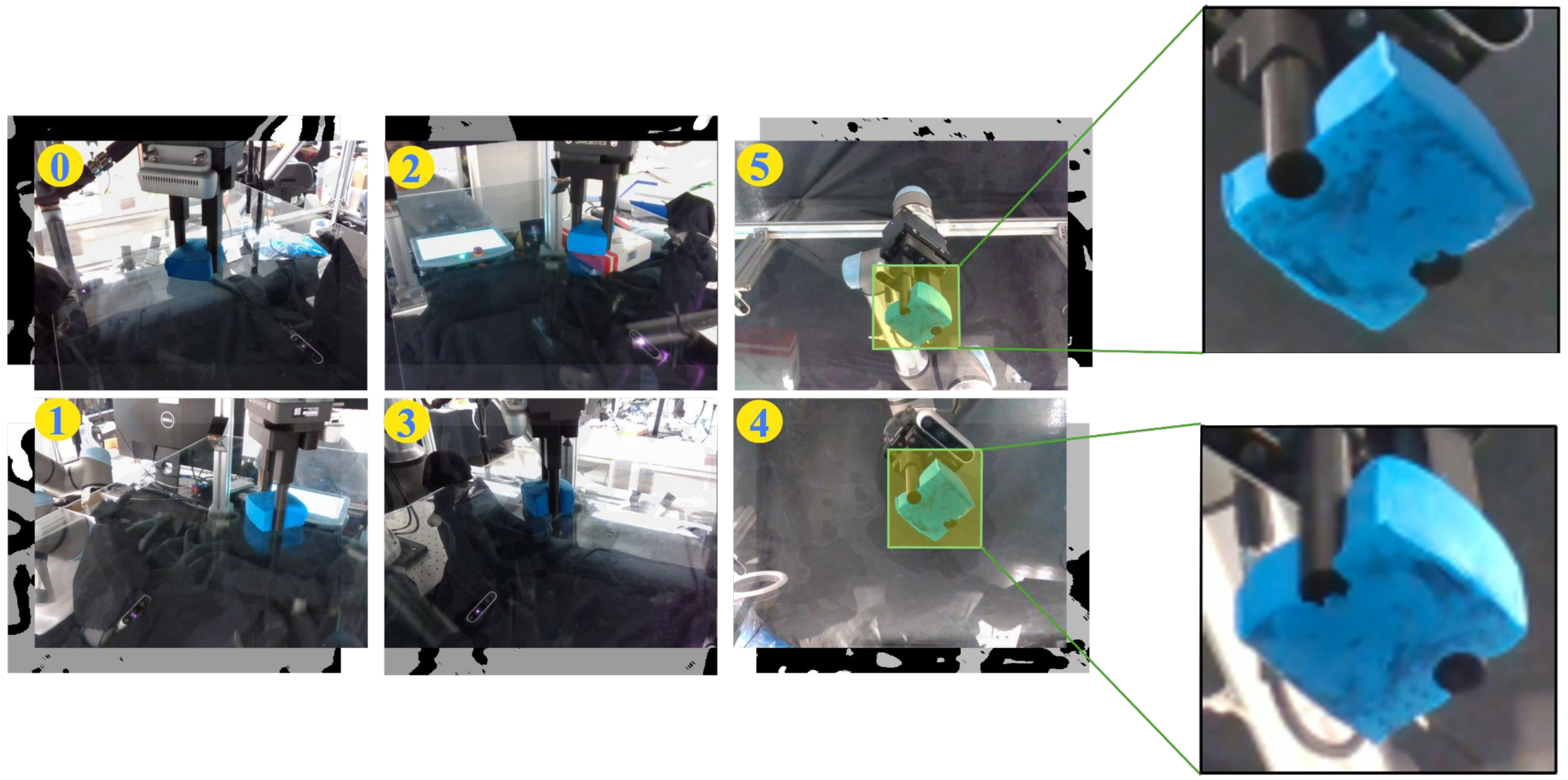
1) High Fidelity Simulation
2) Sim2Real gap
3) Robust Perception in Dynamic environments
4) Multi stage manipulation
5) Dataset and Benchmark standardization

Datasets

[1] Cloth3D



[2] PokeFlex



[3] DOFS

[1] Liu Z, Luo P, Qiu S, Wang X, Tang X. 2016. Deepfashion: Powering robust clothes recognition and retrieval with rich annotations. In 2016 IEEE Conference on Computer Vision and Pattern Recognition, pp. 1096–104. Piscataway, NJ: IEEE
[2] Obrist, J., Zamora, M., Zheng, H., Zarate, J., Katzschmann, R. K., & Coros, S. (2024). PokeFlex: Towards a Real-World Dataset of Deformable Objects for Robotic Manipulation. arXiv preprint arXiv:2409.17124.
[3] Zhang, Z., Chu, X., Yunxi, T., & Au, K. W. S. (2024). DOFS: A Real-world 3D Deformable Object Dataset with Full Spatial Information for Dynamics Model Learning. CoRL Workshop on Learning Robot Fine and Dexterous Manipulation: Perception and Contro
Retrieved from https://openreview.net/forum?id=QADznDlGM4

Thank you!

Next Lecture:
Student Lecture 5
Multisensory and Multimodal Learning + Manipulation

DeepRob

[Group 1] Lecture 04

Pranay, Aditya, Siddharth

Deformable Object Manipulation

University of Minnesota