CIFellows 2020-2021

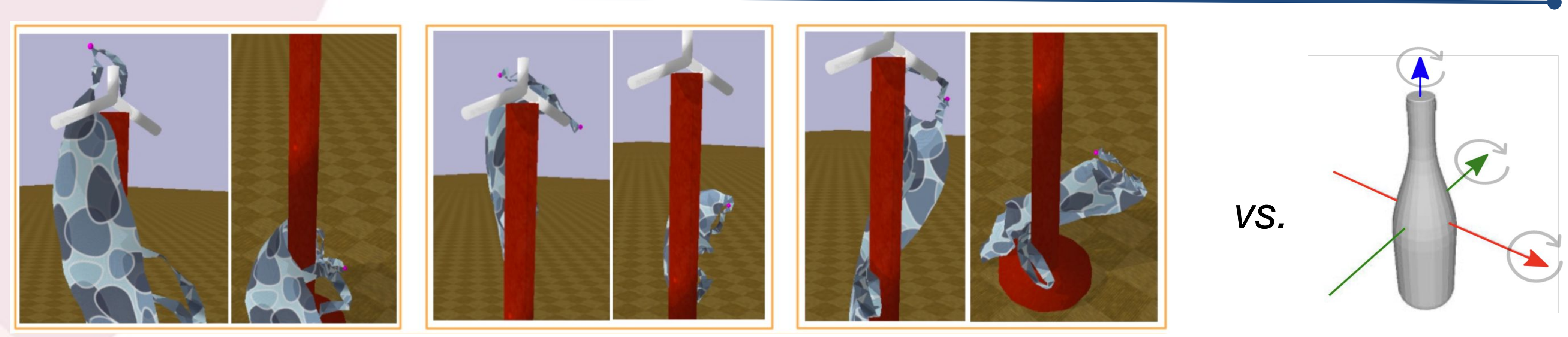
Computing Innovation Fellows

Distributional Representations and Differentiable Learning for Deformable Objects in Robotics

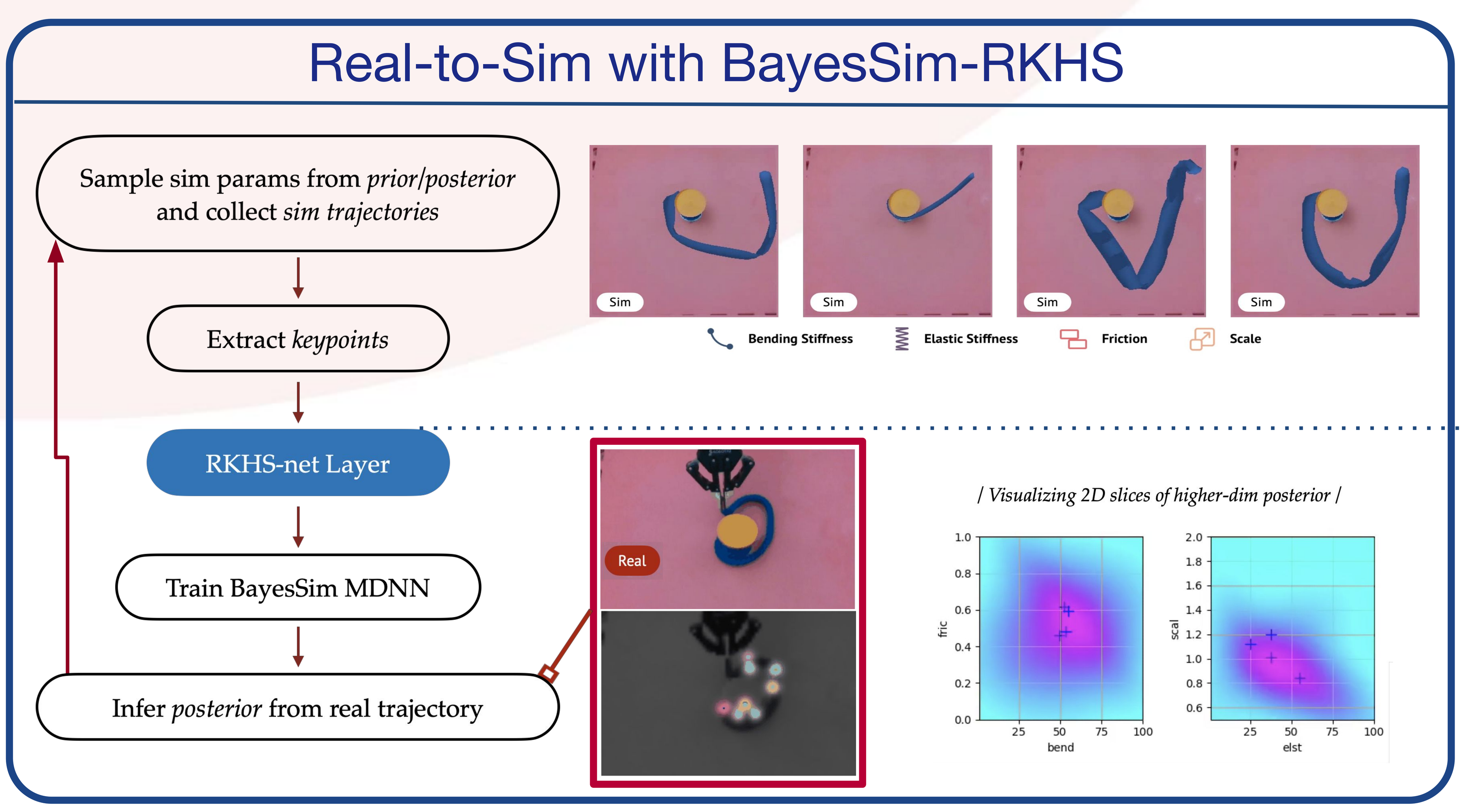
Rika Antonova @ Stanford University

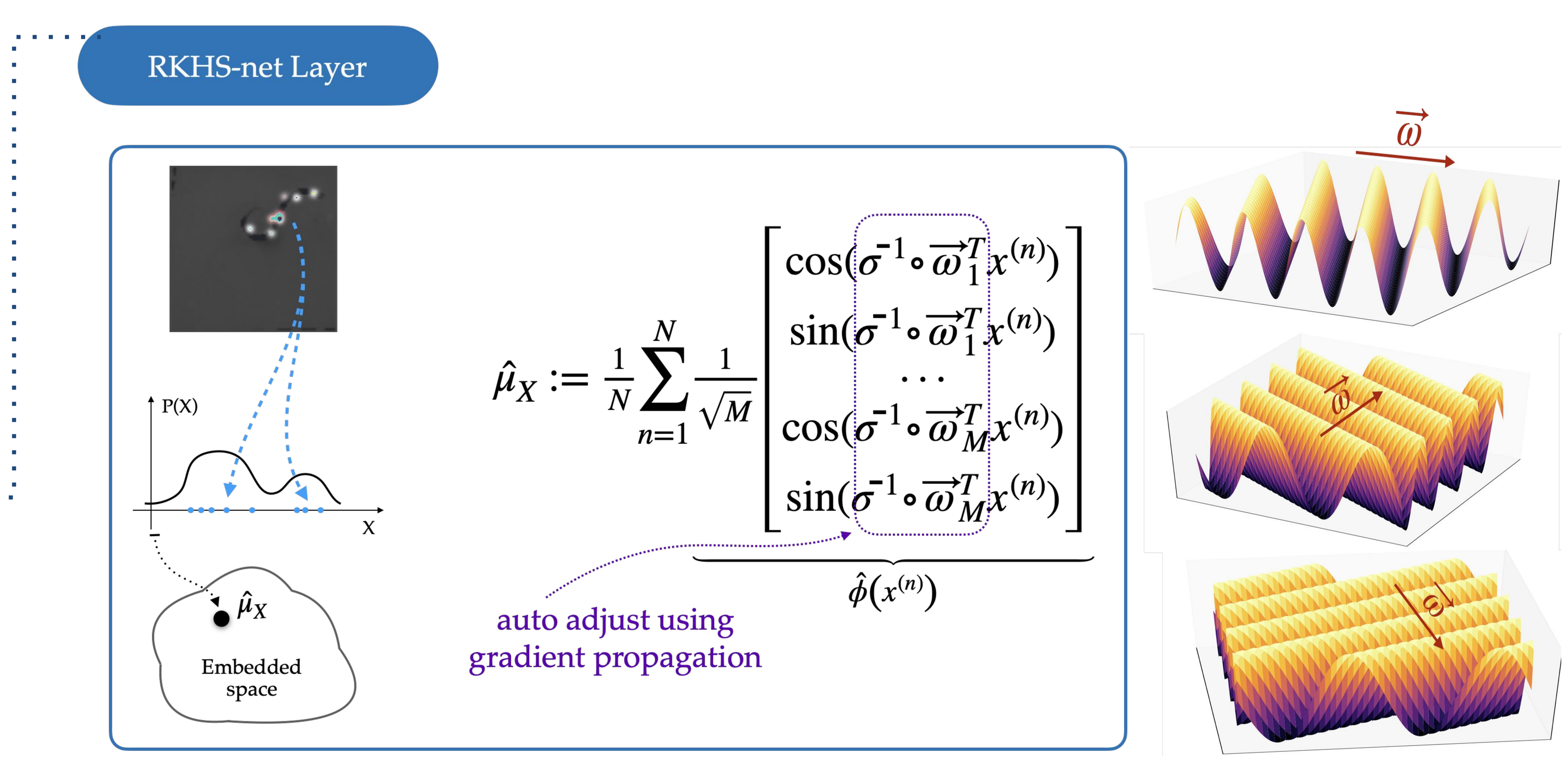
What is difficult about deformables?

- Potentially infinite number of degrees of freedom versus 6 degrees for rigid objects
- Self-occlusions, challenging dynamics (even if using low-dimensional embeddings)



'Real-to-sim' : automatically tune simulators with deformables to resemble reality; enable large-scale policy learning





$$\langle\ \phi(x)\ ,\ \phi(x')\ \rangle_{\mathcal{F}} \approx\ \hat{\phi}(x)^T\hat{\phi}(x')$$

With $\vec{\omega} \sim \mathcal{N}(0,I)$ can approximate an RBF kernel

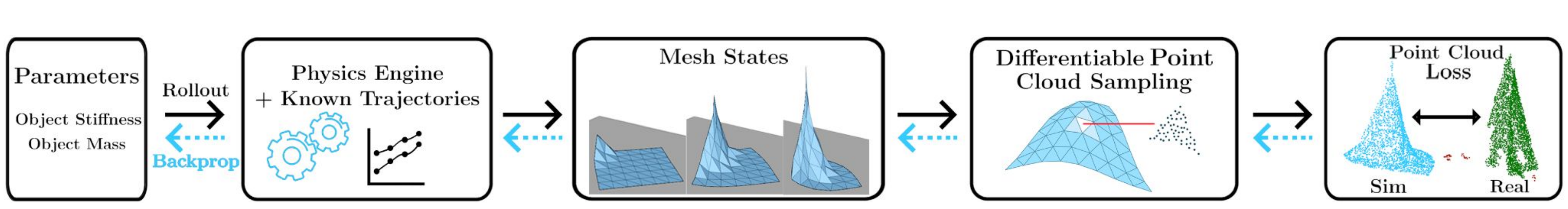
Extract keypoints from deformables with unsupervised methods; keypoints are unordered & can appear on various object parts.

Interpret keypoints as noisy samples from partially observed state distribution, then embed into an infinite-dimensional space to get:

❖ permutation invariance ❖ robustness to noise ❖ convenient distance metric ❖ continuity

R Antonova, J Yang, P Sundaresan, D Fox, F Ramos, J Bohg. A Bayesian Treatment of Real-to-Sim for Deformable Object Manipulation. IEEE Robotics and Automation Letters (RA-L) 2022.

Current and future collaborations: real-to-sim with differentiable simulators & reinforcement learning with scalable simulators



tinyurl.com/diffcloud

github.com/contactrika/dedo

R Antonova, P Shi, H Yin, Z Weng, D Kragic. Dynamic Environments with Deformable Objects. NeurIPS 2021 (Datasets and Benchmarks).

Home-to-Habitat: Household Tasks with Deformables in AI Habitat. An industry collaboration with Meta AI.

CRA Computing Research Association
CCC Computing Community Consortium Catalyst
NSF