

Density-based Feasibility Learning with Normalizing Flows for Introspective Robotic Assembly

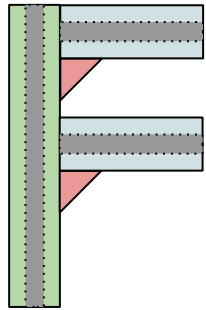
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Stephan Günnemann² and Rudolph Triebel¹

¹: Institute of Robotics and Mechatronics, German Aerospace Center (DLR)

²: Technical University of Munich (TUM)



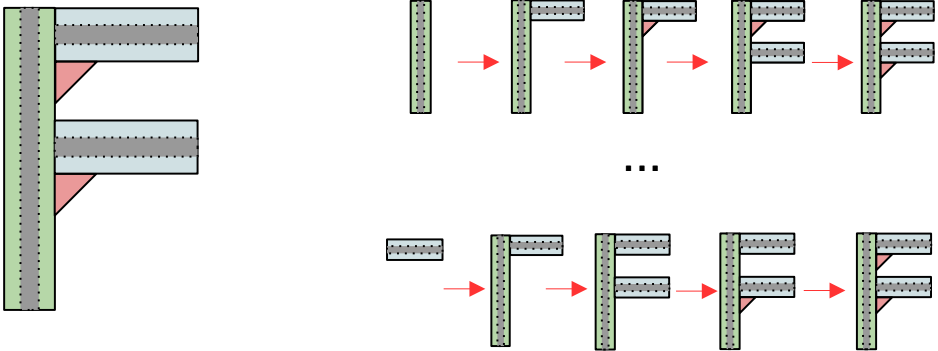
Robotic Assembly



Assembly
Specification



Robotic Assembly



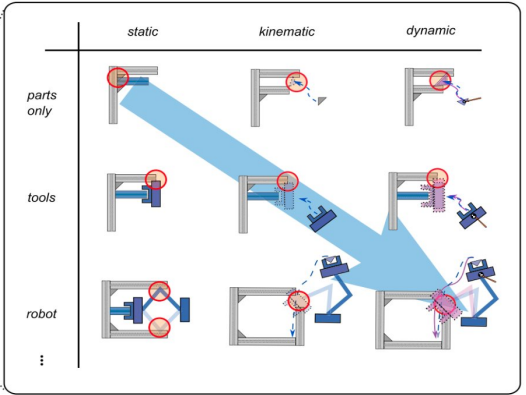
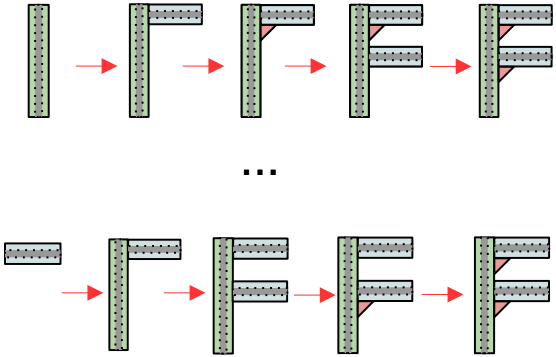
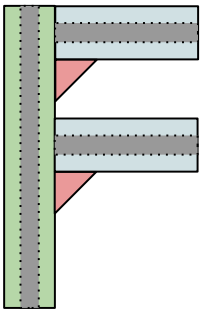
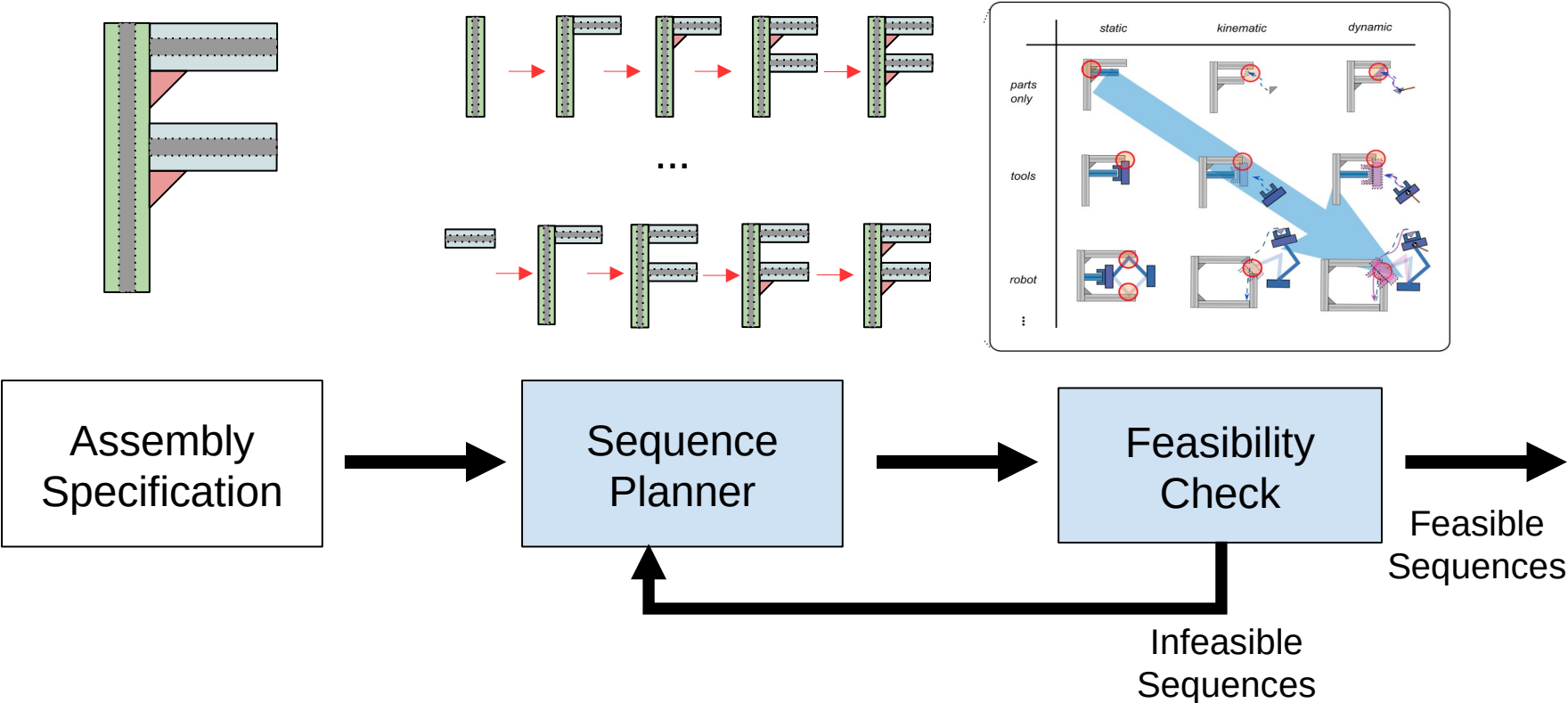
Assembly Specification



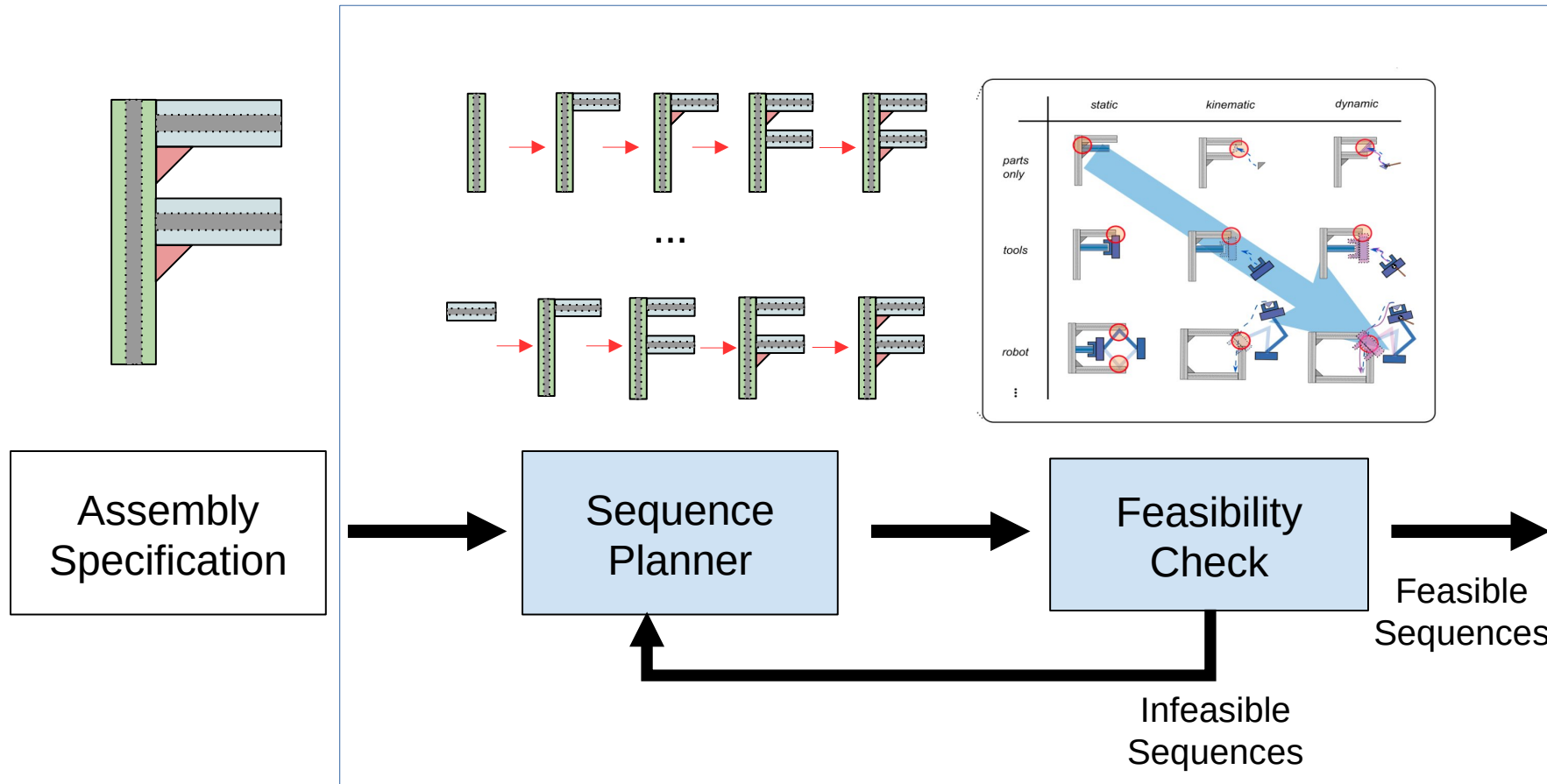
Sequence Planner



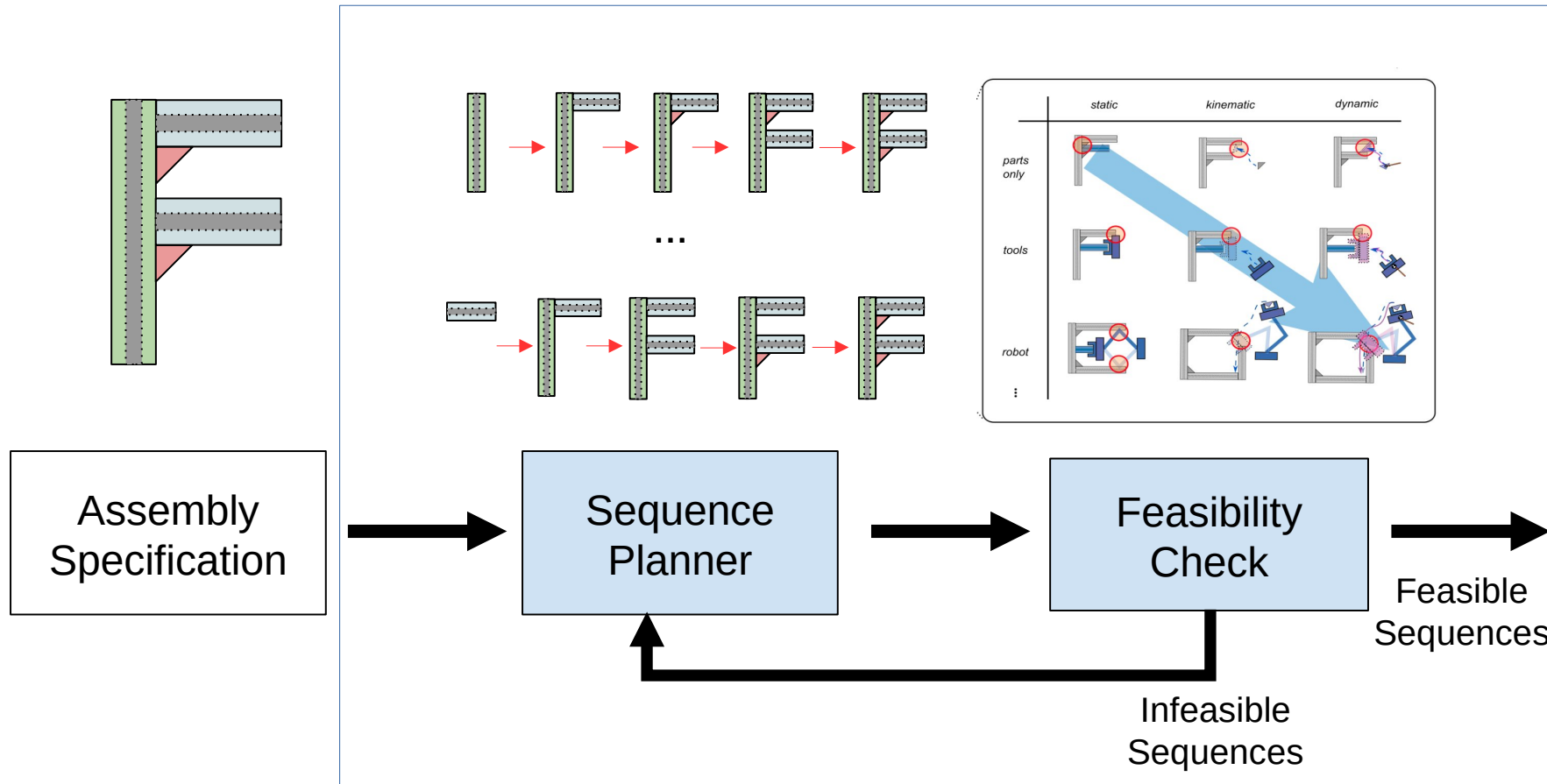
Robotic Assembly



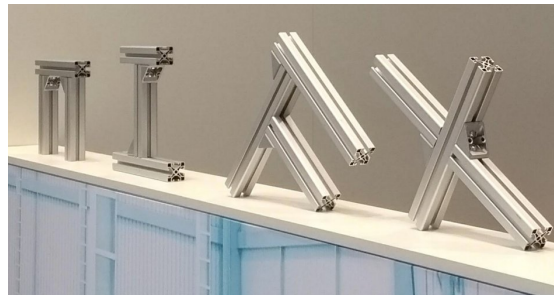
Robotic Assembly



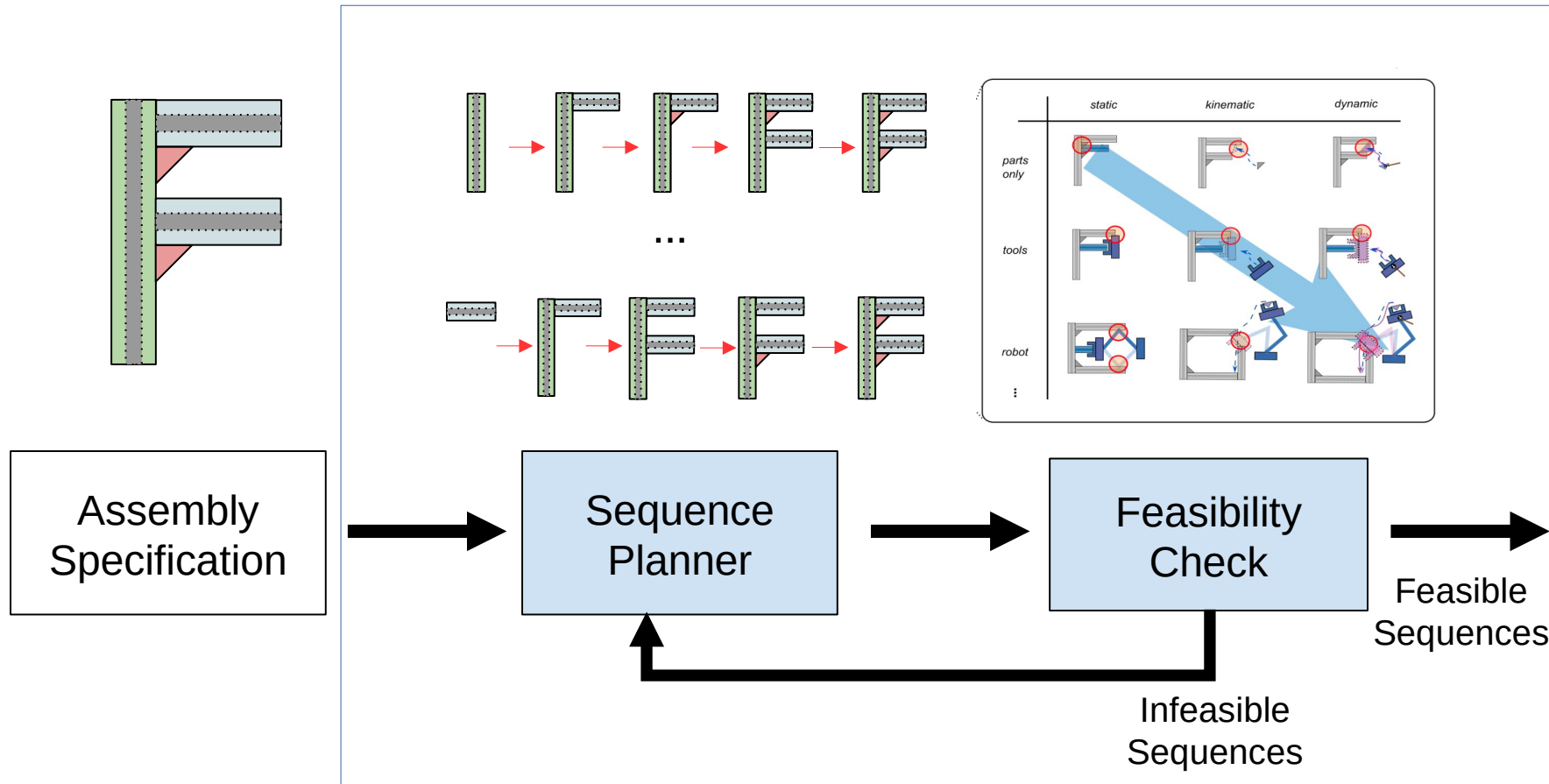
Robotic Assembly



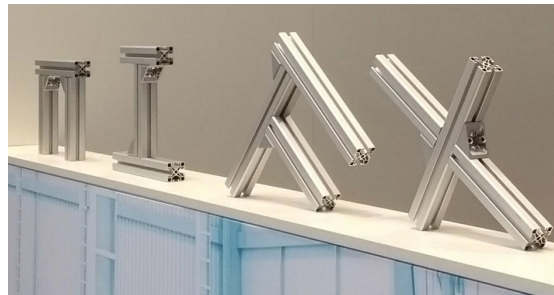
Limited Generalizability



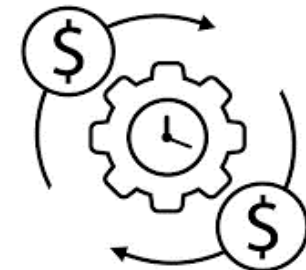
Robotic Assembly



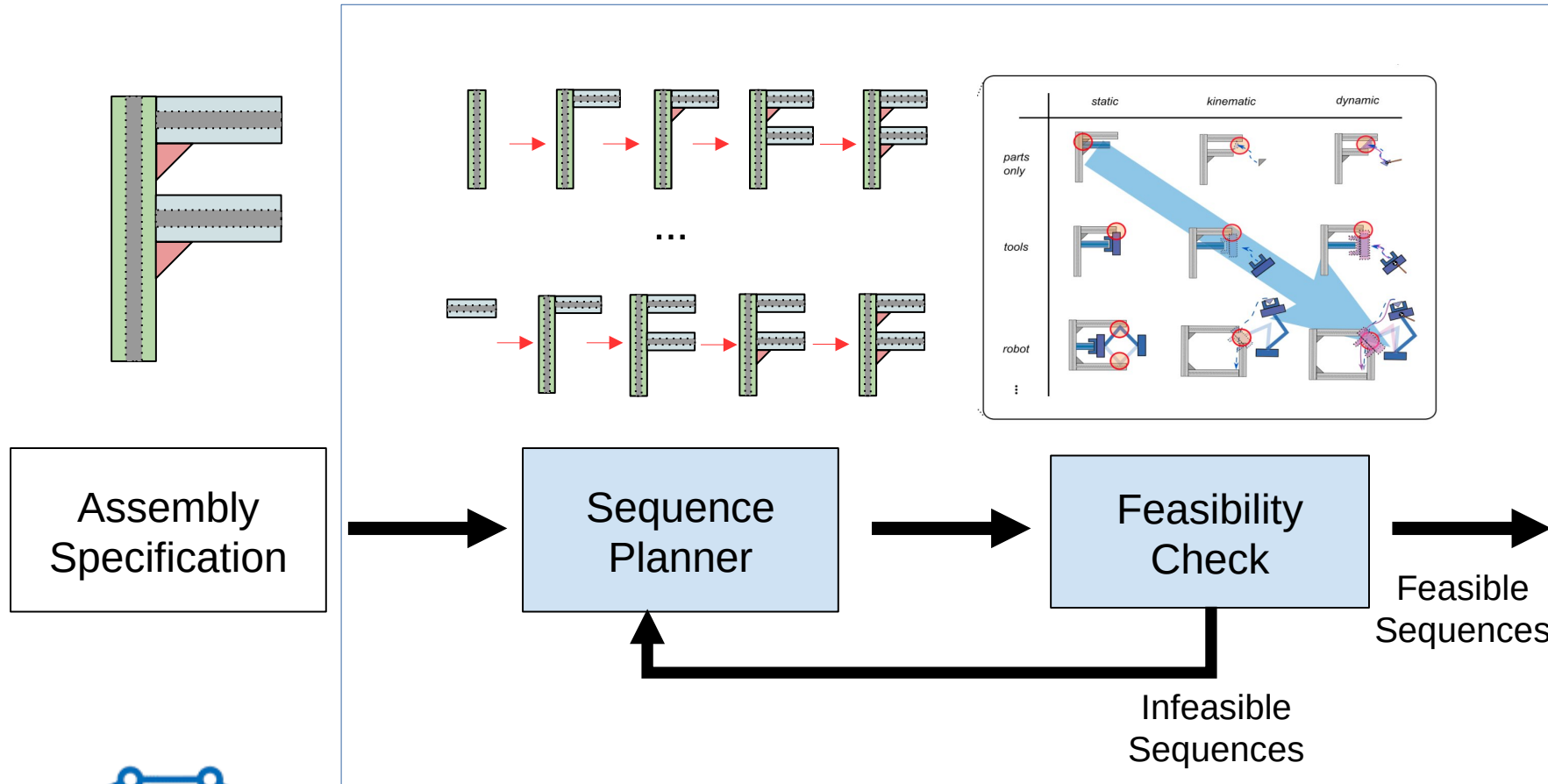
Limited Generalizability



Low Run-time Efficiency

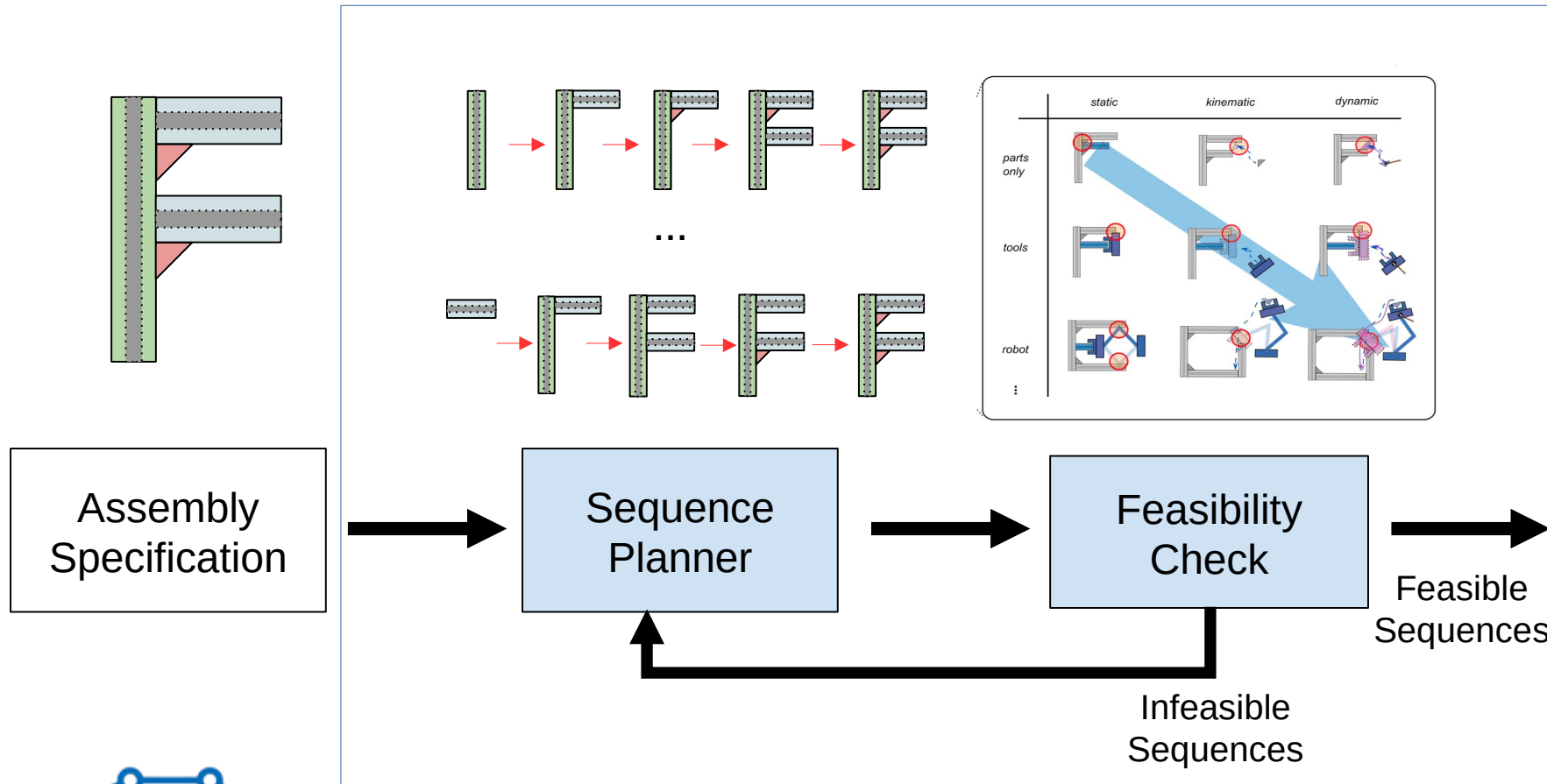


Data-driven Robotic Assembly

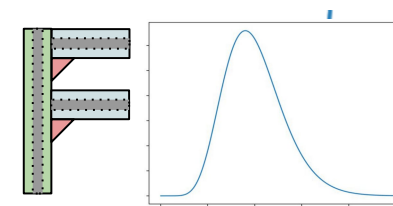


Data-driven approaches for
Generalizability & Efficiency.

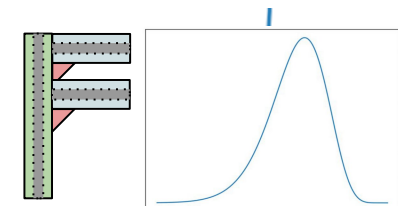
Data-driven Robotic Assembly



Data-driven approaches for **Generalizability** & **Efficiency**.

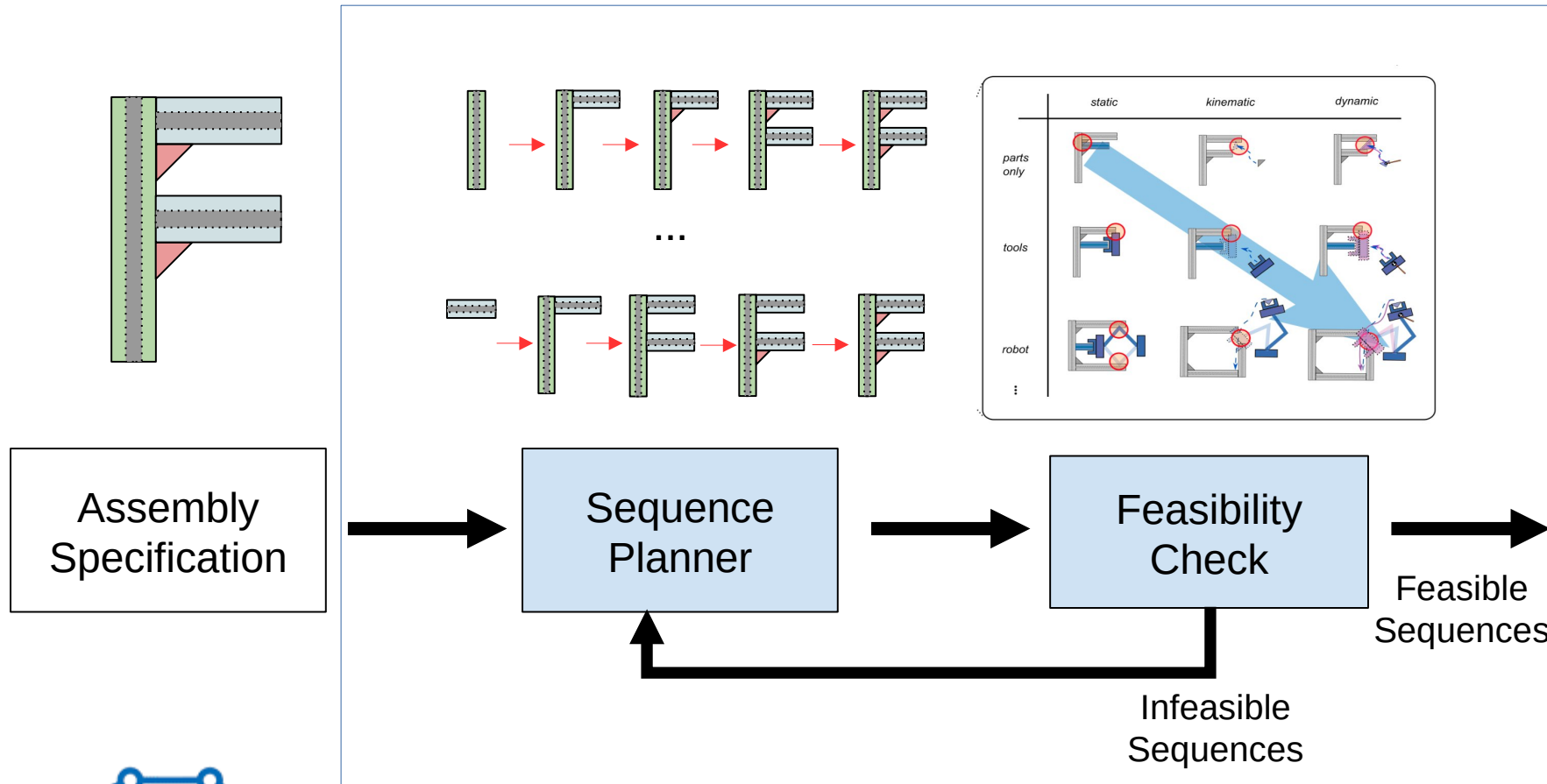


Training Dist.



Test Dist.

Data-driven Robotic Assembly



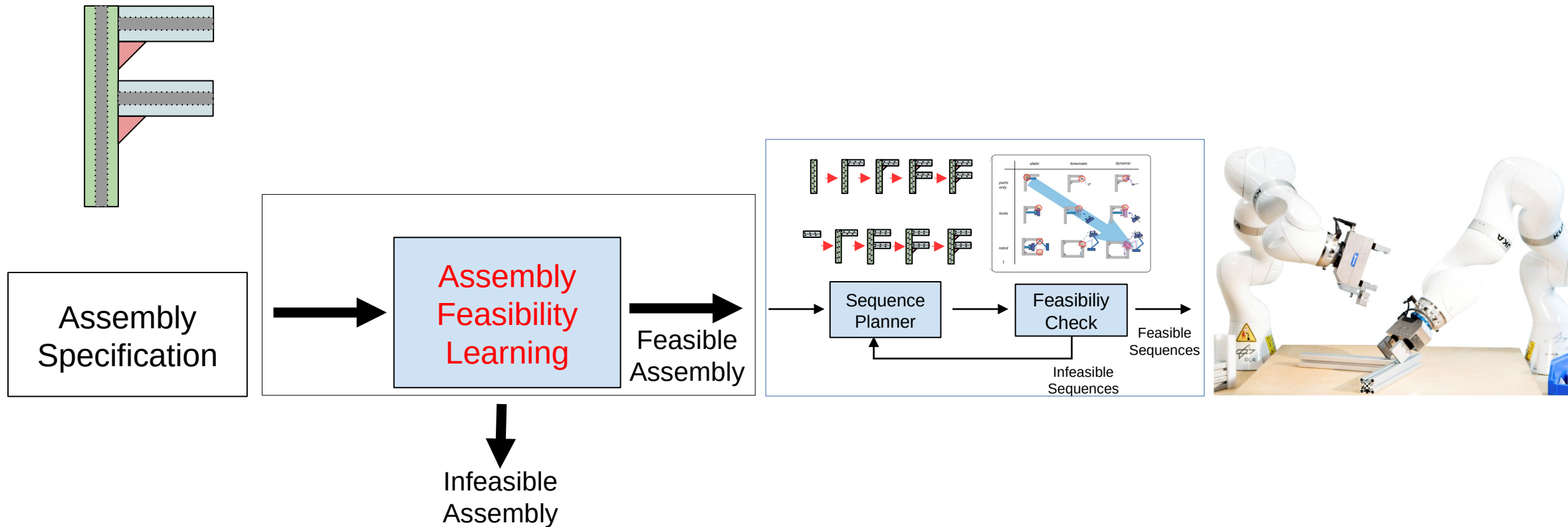
Data-driven approaches for **Generalizability** & **Efficiency**.



hard to collect **sufficient** training data;

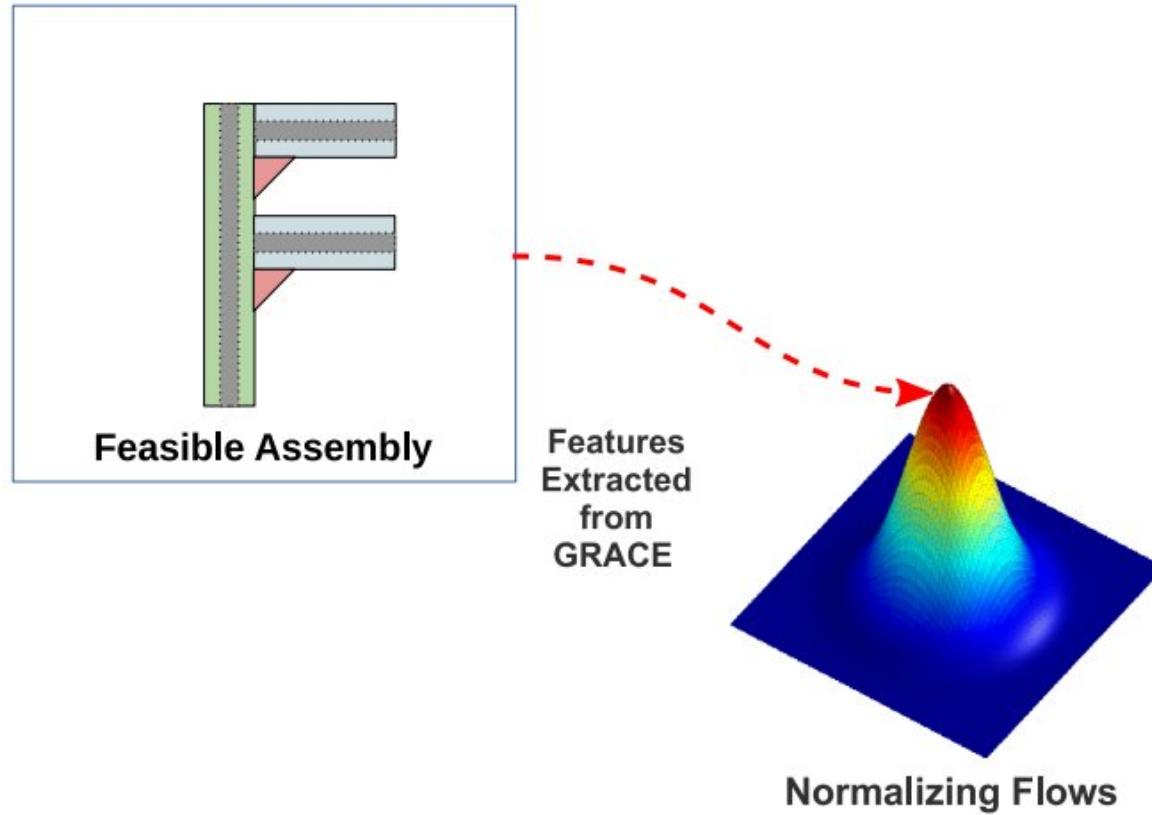


Introspective Robotic Assembly – Assembly Feasibility Learning



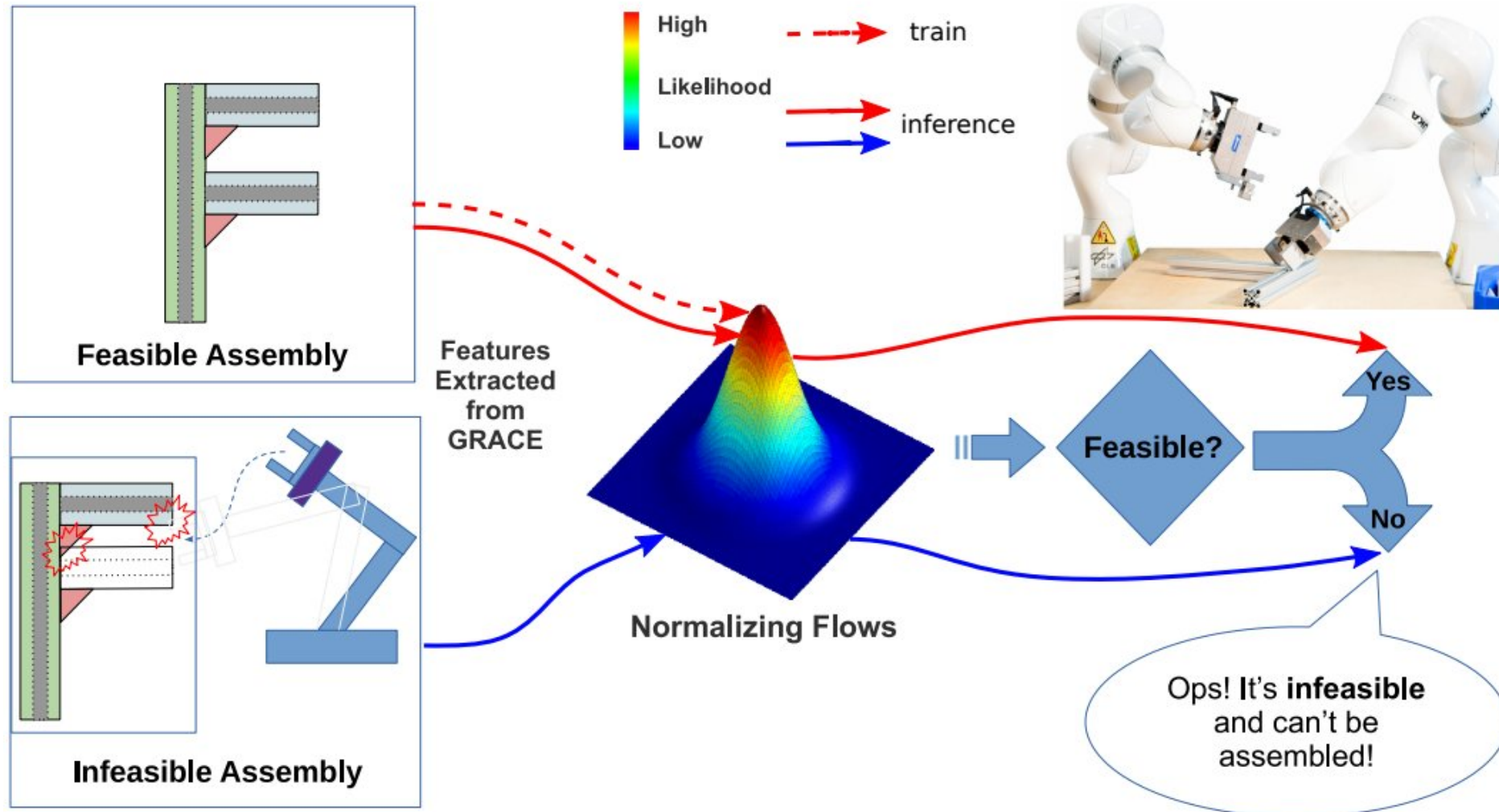
Introspective robotic assembly:
Assembly feasibility learning as Out-of-distribution (OOD) detection based on **purely feasible cases**.

Assembly Feasibility Learning via Density Estimation



- Training: **Maximizing** the likelihoods of feasible assemblies.

Assembly Feasibility Learning via Density Estimation



- Training: **Maximizing** the likelihoods of feasible assemblies.
- Test: Detecting infeasible assemblies with **low** likelihoods.

Density Estimation with Normalizing Flows



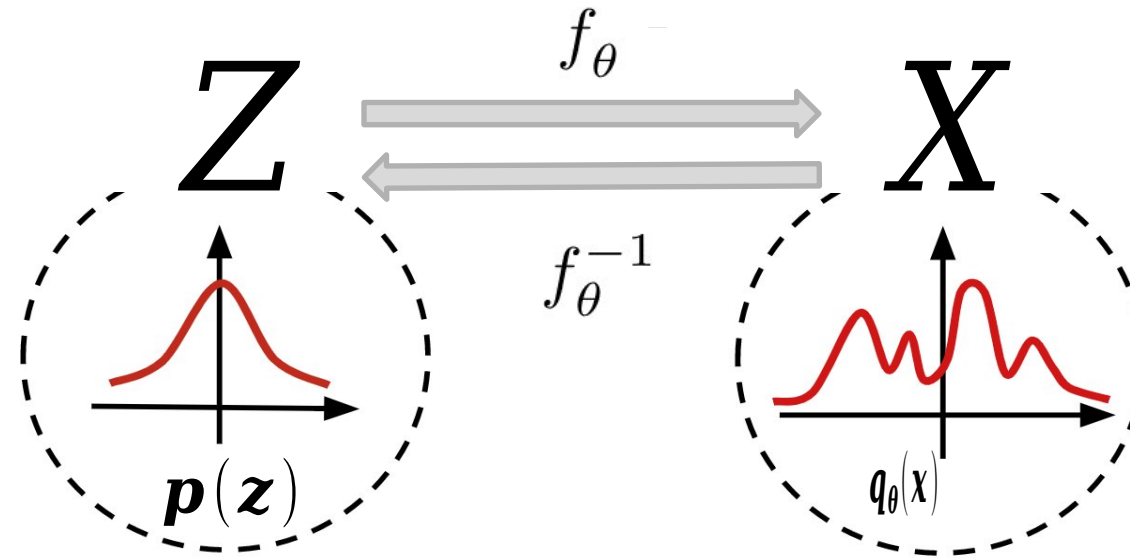
Normalizing flows are a popular class of deep generative models:

- flexible density estimation;
- fast and exact likelihoods computation;

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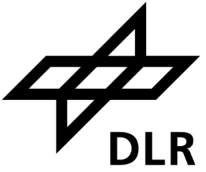


$$\log q_\theta(\mathbf{x}) = \log p(f_\theta^{-1}(\mathbf{x})) + \log \left| \det \left(\frac{\partial f_\theta^{-1}(\mathbf{x})}{\partial \mathbf{x}} \right) \right|$$

Log Likelihood of
base distribution

Log Determinant
of Jacobians

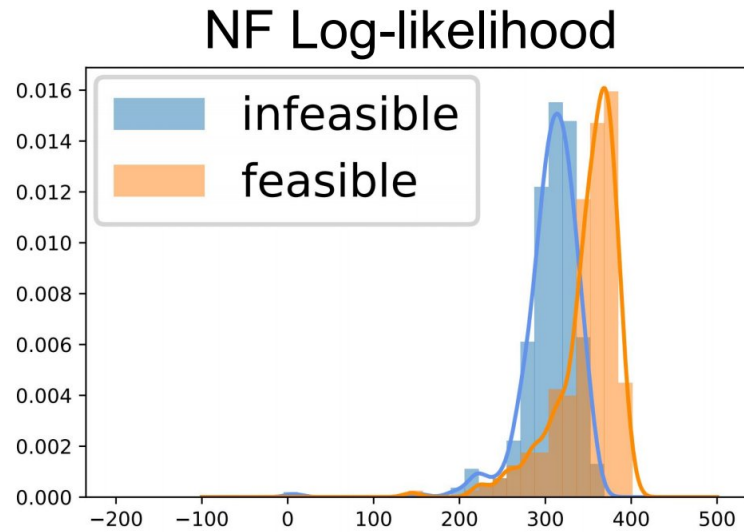
Experiment - Infeasible Assemblies Detection



	Area Under ROC \uparrow	
	A_5	A_6
NF, 749 layers, gaussian base	0.85	0.83
NF, 109 layers, resampled base	0.83	-
OC-SVM [4]	0.74	0.59
Baseline (size of predicted set)	0.61	0.57

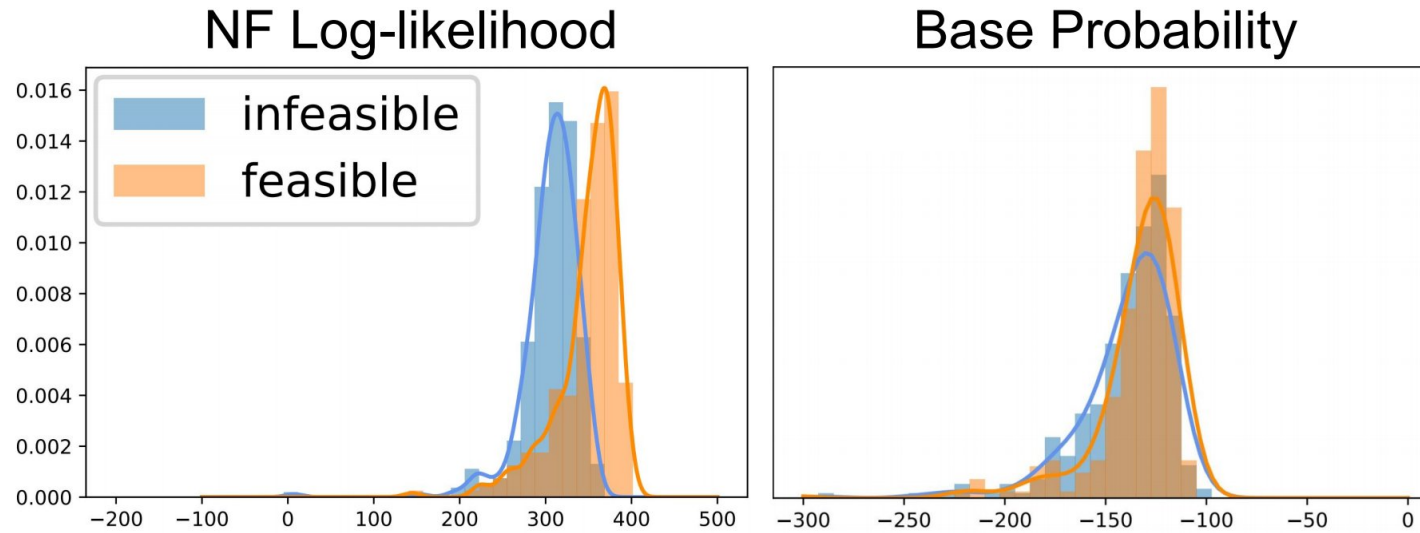
A_n : assemblies with n parts.

Ablation – Normalizing Flow Density Estimation



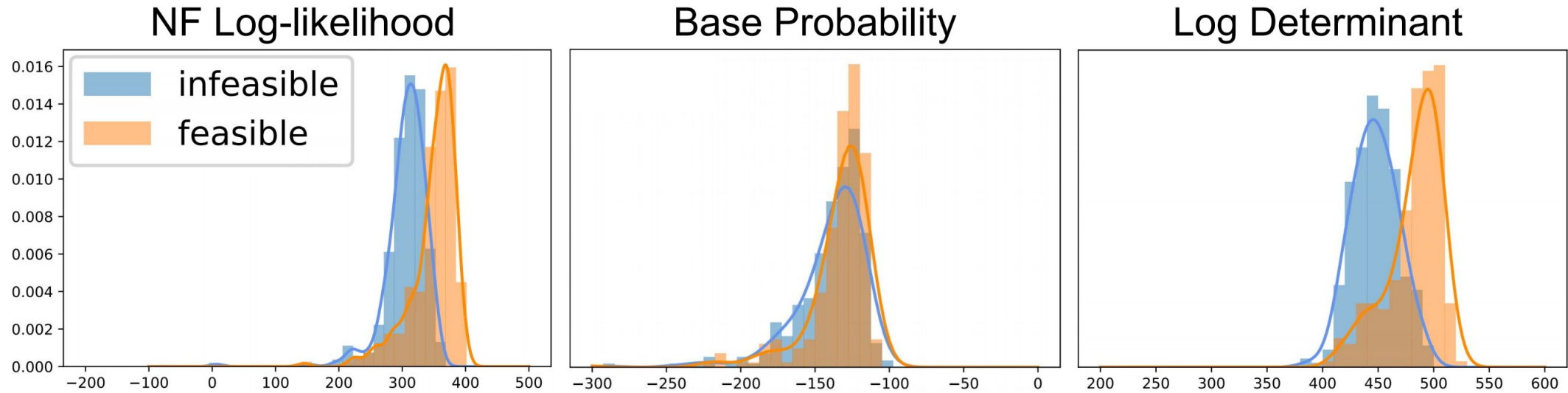
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Arrows from the equation point to the corresponding histograms: the first term points to 'Base Probability', and the second term points to 'Log Determinant'.

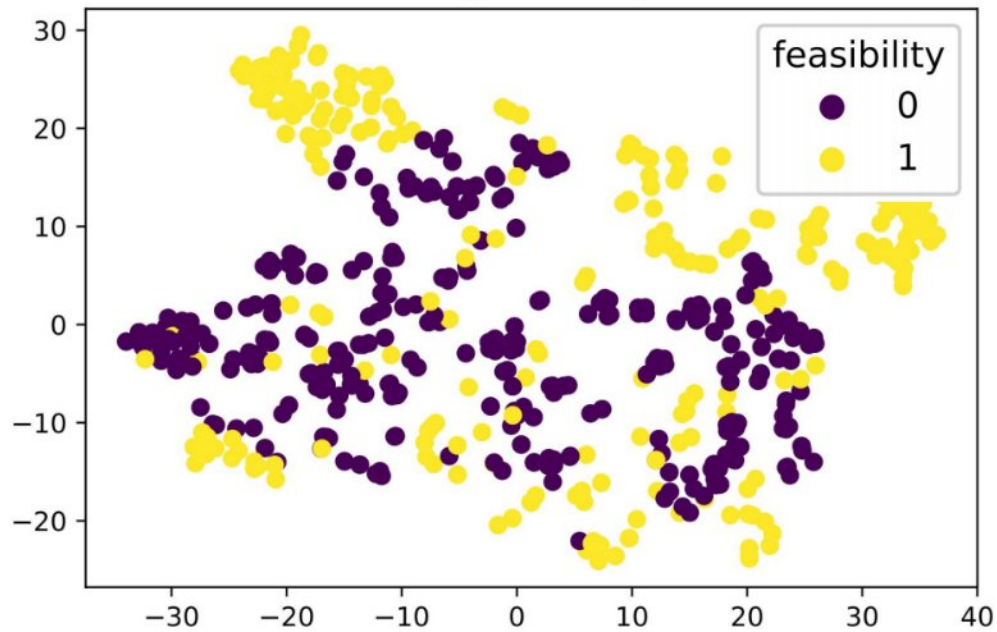
- Log Determinants of Jacobians is the main contributing factor to the final likelihoods.

Ablation – Normalizing Flow Transformation



T-SNE Visualization

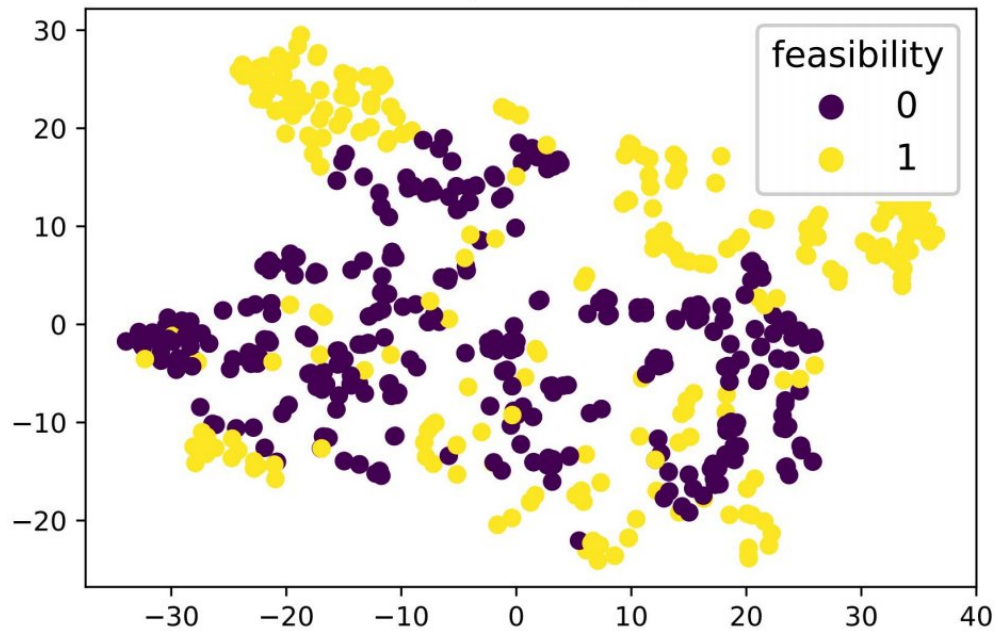
Flow Input Space



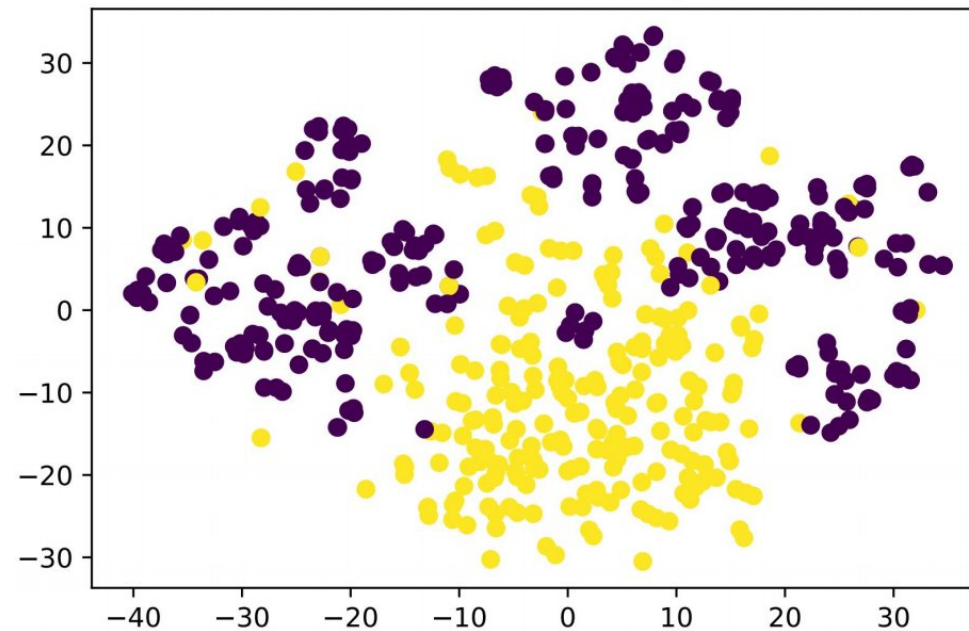
Ablation – Normalizing Flow Transformation

T-SNE Visualization

Flow Input Space



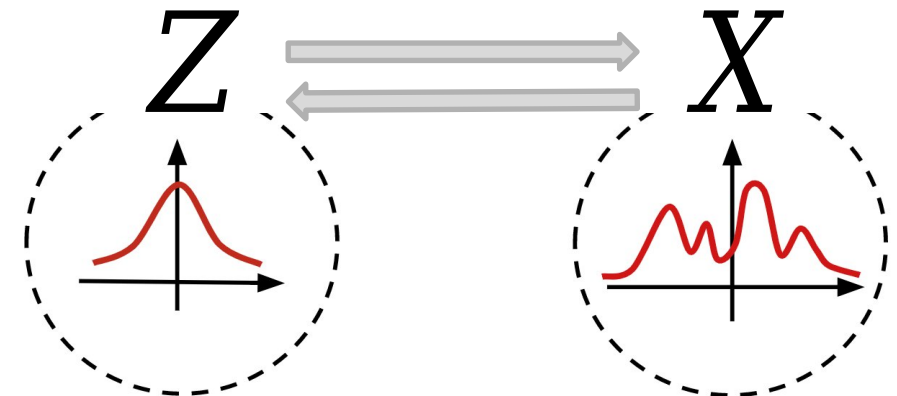
Flow Latent Space



- Feasible assemblies are pulled together and clustered more compactly when compared to those in the input space before the flow transformation.

Conclusion

- Raising Importance of **Introspection** for data-driven approaches in robotic assembly sequence planning (RASP).
- Formulating feasibility learning as Out-of-Distribution (OOD) detection with normalizing flows based on **only** feasible assemblies;
- Validating on **infeasible assemblies detection** task in simulation, with ablation studies on the working mechanisms of the flows.
- **Explaining** the in/feasibility based on NFs as future work.



Thank you for your attention!