Bayesian Inverse Physics for Neuro-Symbolic Robot Learning

Physics + Uncertainty + Program Synthesis = Efficient Safe Adaptable Learning

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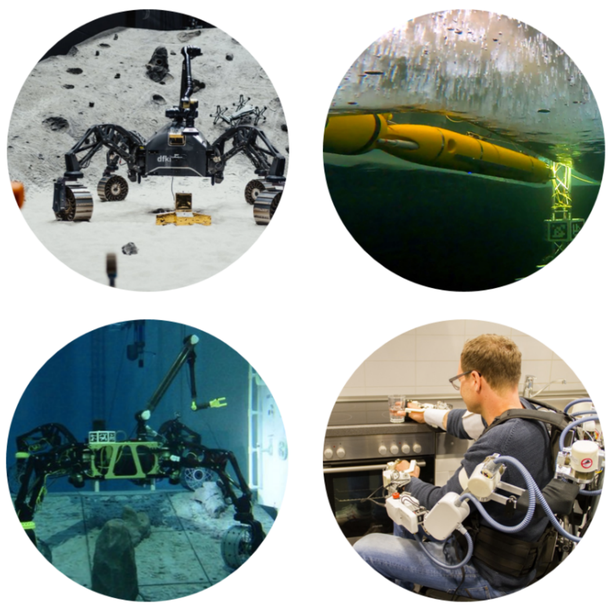
Summary

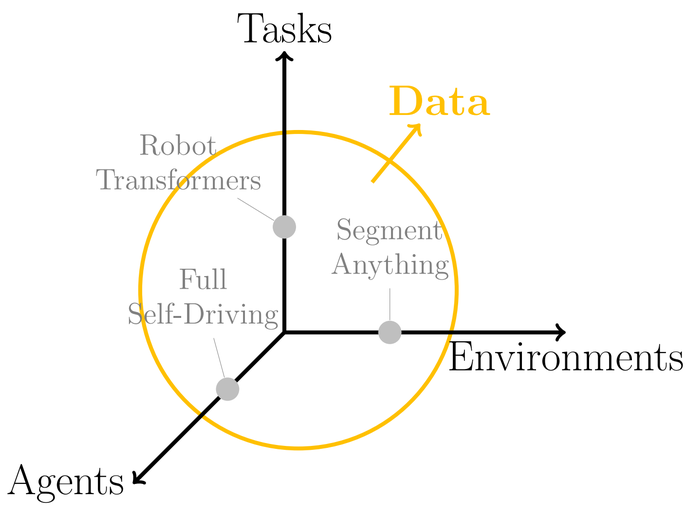
- Real-world robotic applications demand learning paradigms that are **adaptive, safe, and data-efficient**.
- Deep Learning & Foundation Models struggle with **generalization, safety, and sample efficiency**.
- To develop the right framework for robot learning, we ask the following questions:
  1. Why should learning algorithms ignore the most accurate predictive models of our world: **physics**?
  2. Why should we trust the probabilities of a model we do not understand?
- We propose a framework combining and scaling physics, program synthesis and deep learning.

A Neuro-Symbolic Framework for Robotics

1. **Differentiable Physics:** to build efficient world models that enhance generalization and consistency.
2. **Bayesian Inference:** Posterior sampling and variational inference for uncertainty-aware safe models.
3. **Program Synthesis:** For building higher-level abstractions and enabling rapid adaptation to new tasks.



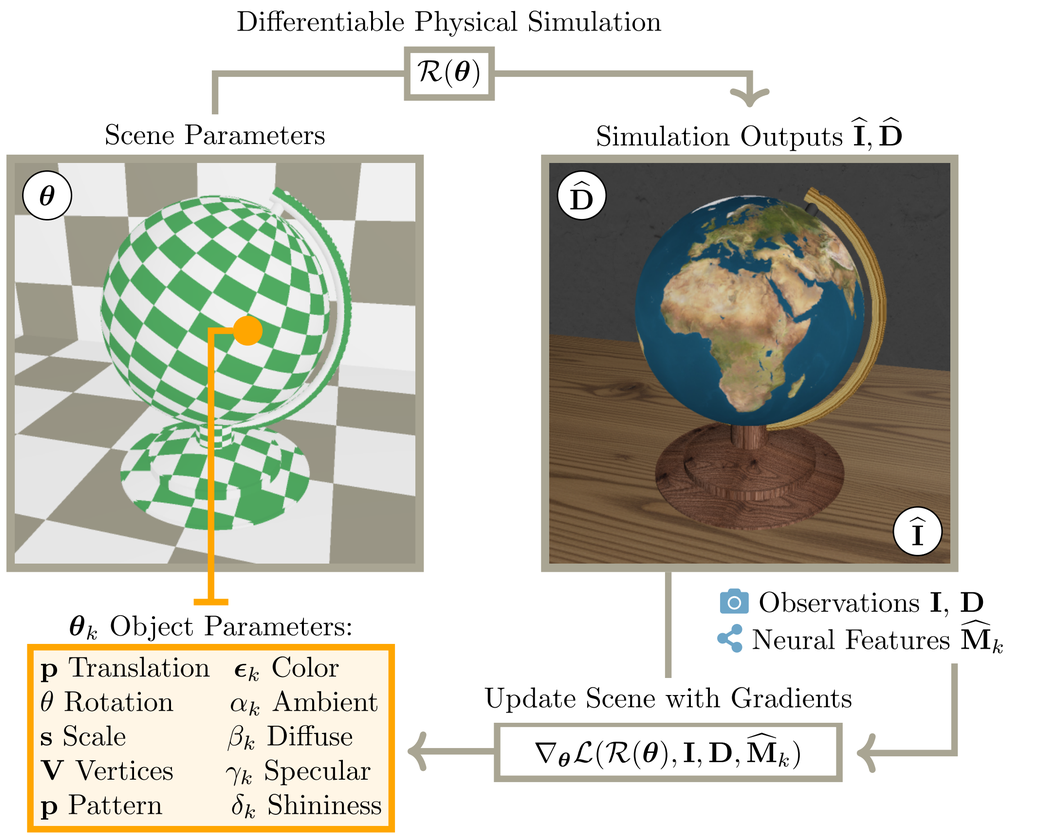
Why are Foundation Models not enough for Robotics?



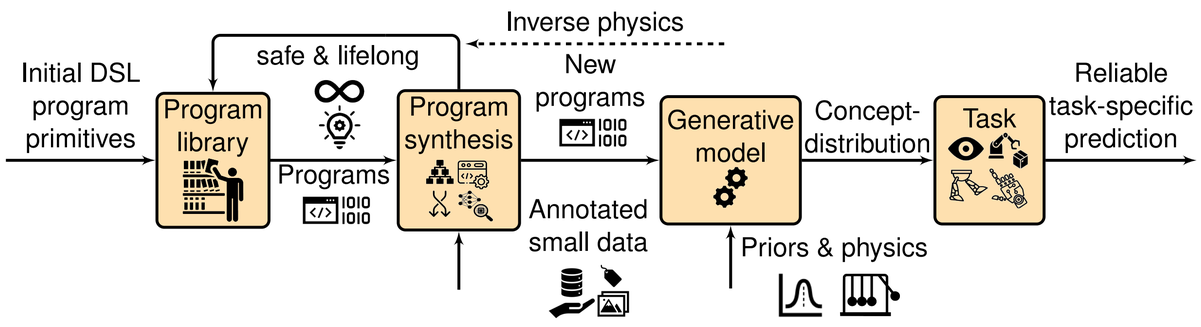
Generalization Axes in Robotics

1. Performance increases with data, but remains insufficient for autonomy.
2. Learning models shouldn't ignore physics:
   - Most accurate, general models with the shortest description length.
3. We should compute uncertainties of physically consistent models.

Physical World Models

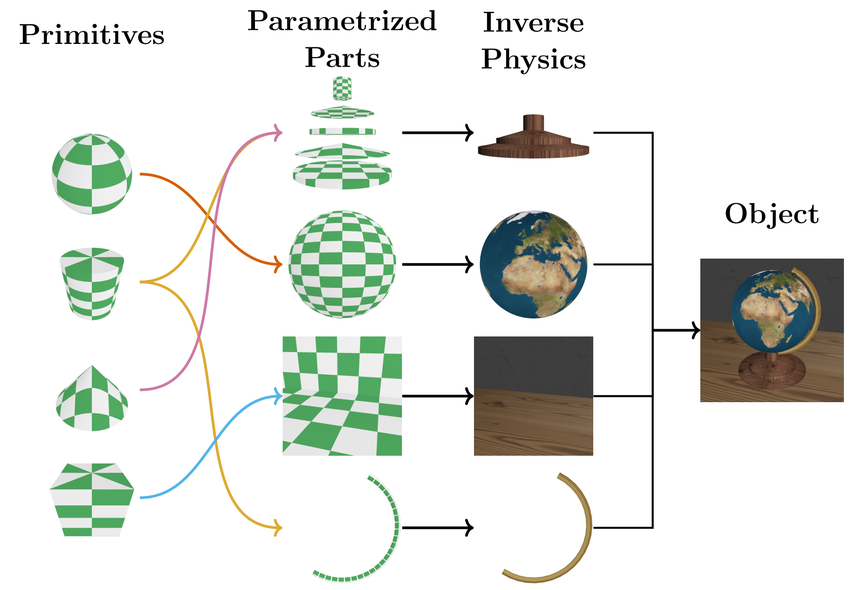


Fusing Physics, Bayesian Inference and Program Synthesis

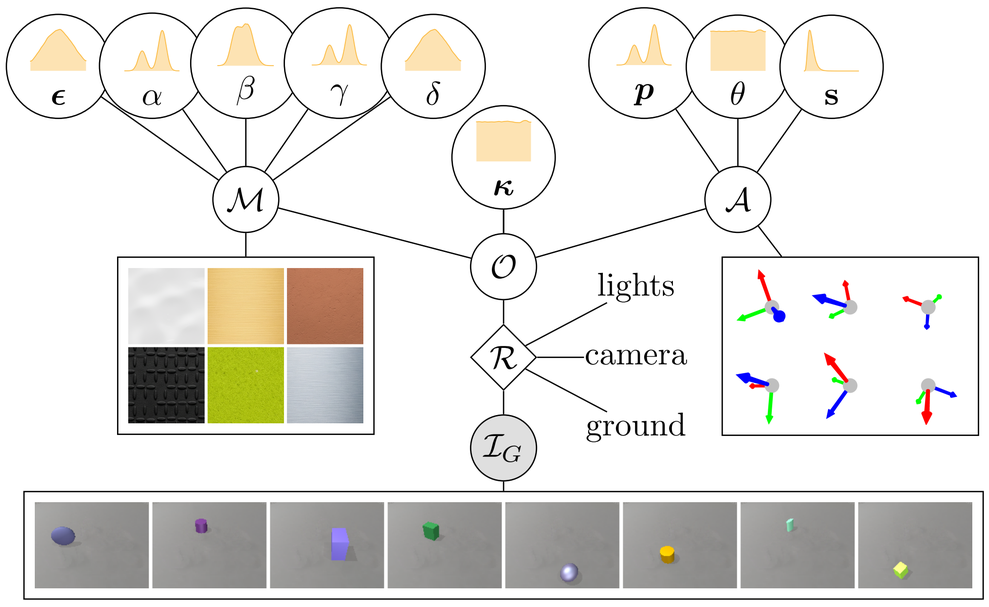


- Specify domain specific languages (DSLs) depending on the task.
- Populate library with physical program primitives.
- Synthesize programs using search and data-driven methods.
- Build probabilistic model using priors & physics.
- Perform inference and solve tasks for robot perception and behavior.

Example of Program Synthesis for Robot Perception



Example of a Physical Generative Model for Perception



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