Continuously Learning Complex Tasks **via Symbolic Analysis** (CoLeSIAw) *

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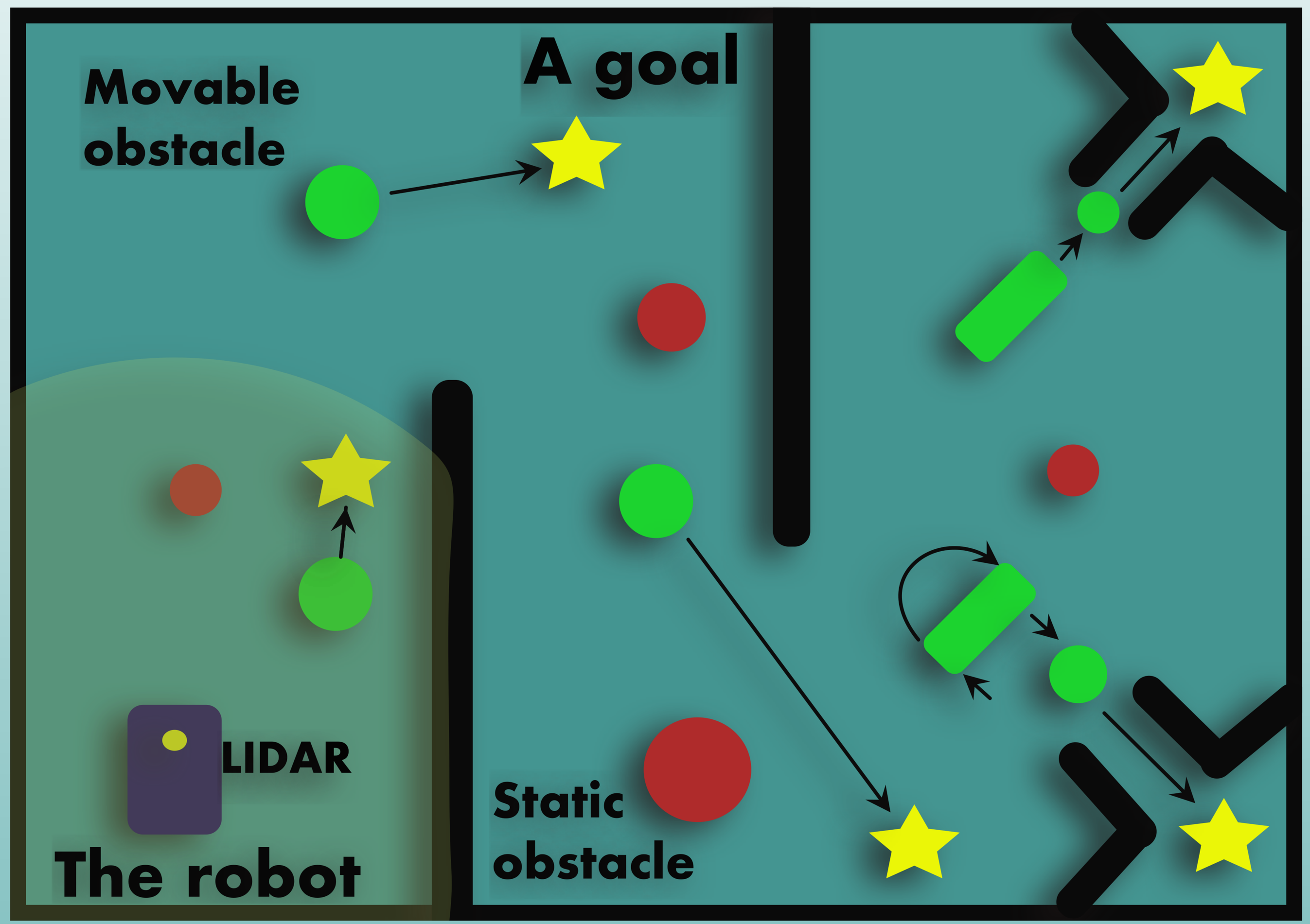
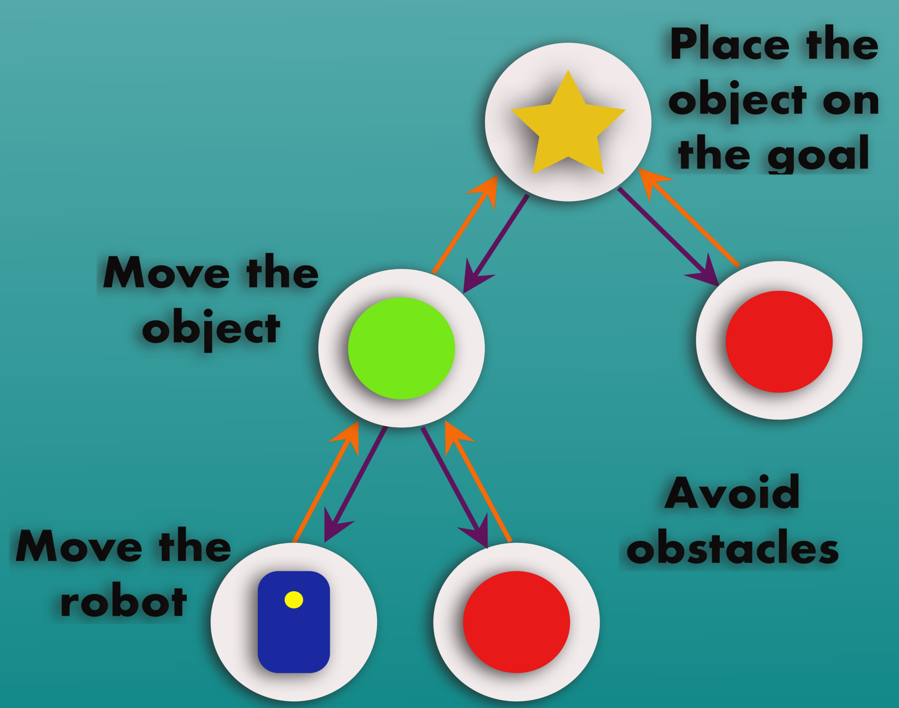
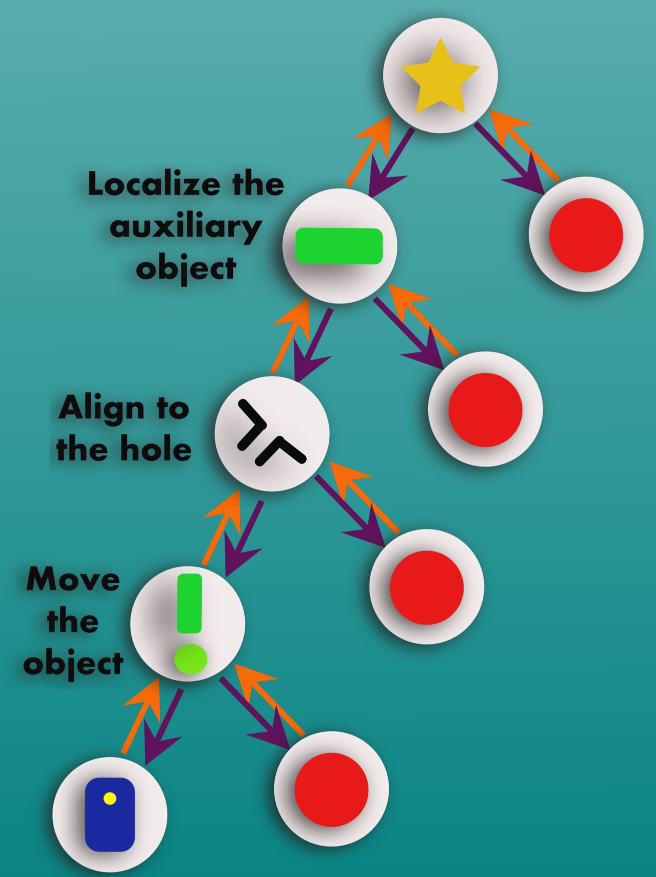
The **Continual learning** problem:

The ability to incrementally learn and expand the knowledge by gaining new skills and expertise.
A system of a mobile robot pushing object to goals could be solved by continual learning.

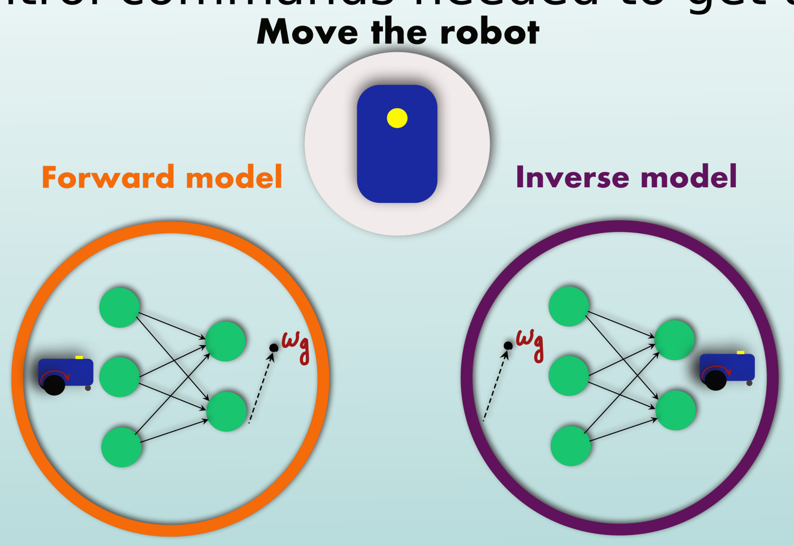


The robot has two cases (1) direct moving of the objects (2) using an auxiliary object to push the goal object to the goal, while avoiding obstacles.
The key idea is to dissect the complex problem into a hierarchy of simple tasks (skills of affordances), the robot will learn the first case, and for the second case will extend the hierarchy, but still use the learned skills.

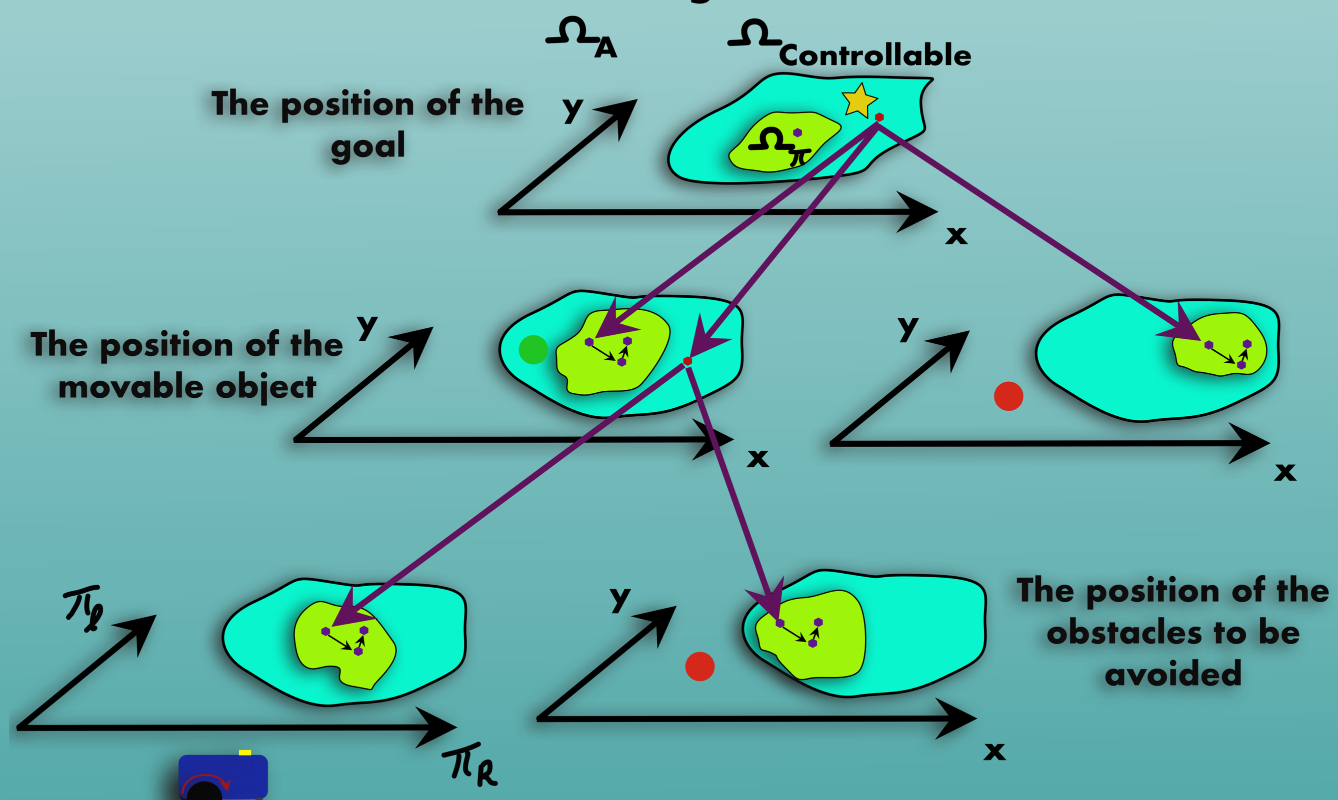




The robot learns two models for each of the skills (affordances) from the hierarchy (1) a **forward model** predicts the consequences of executing an action (2) an **inverse model** outputs the control commands needed to get a desired observation.



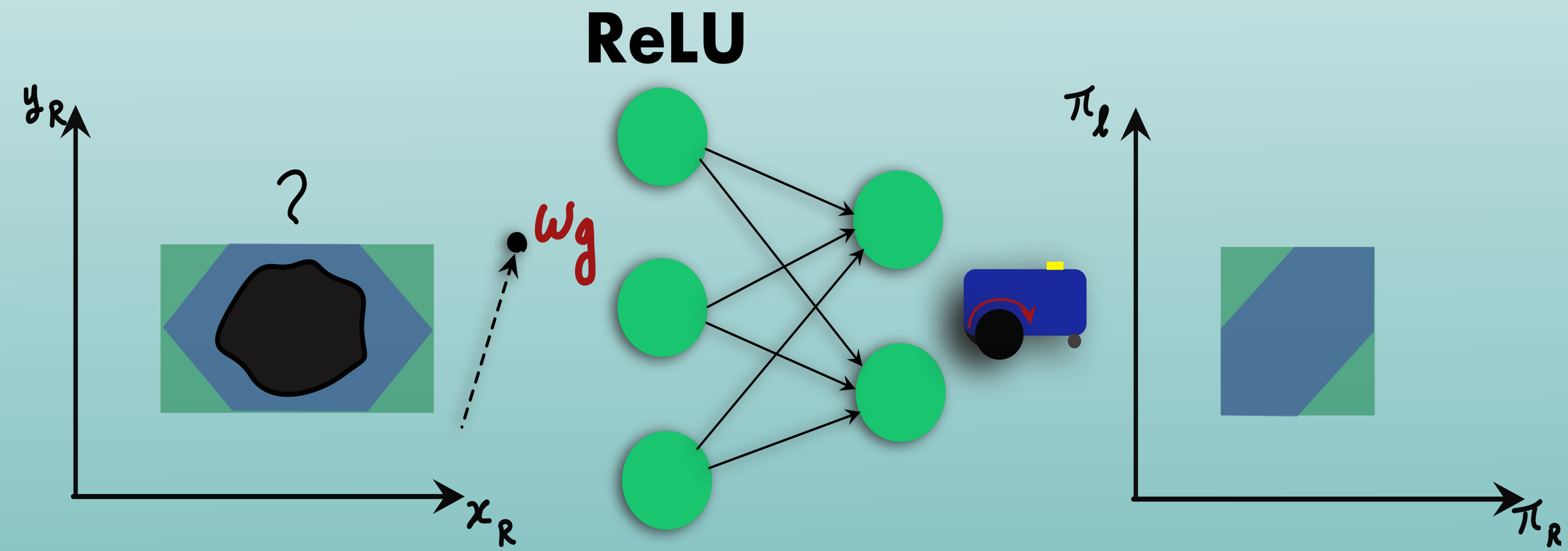
The learned models are used to propagate the states over the hierarchy, if the desired state lies in a controllable region of the observation space, then we could depict the suitable control commands (motor commands or update the plan in our case) for all the affordances to reach the goal.



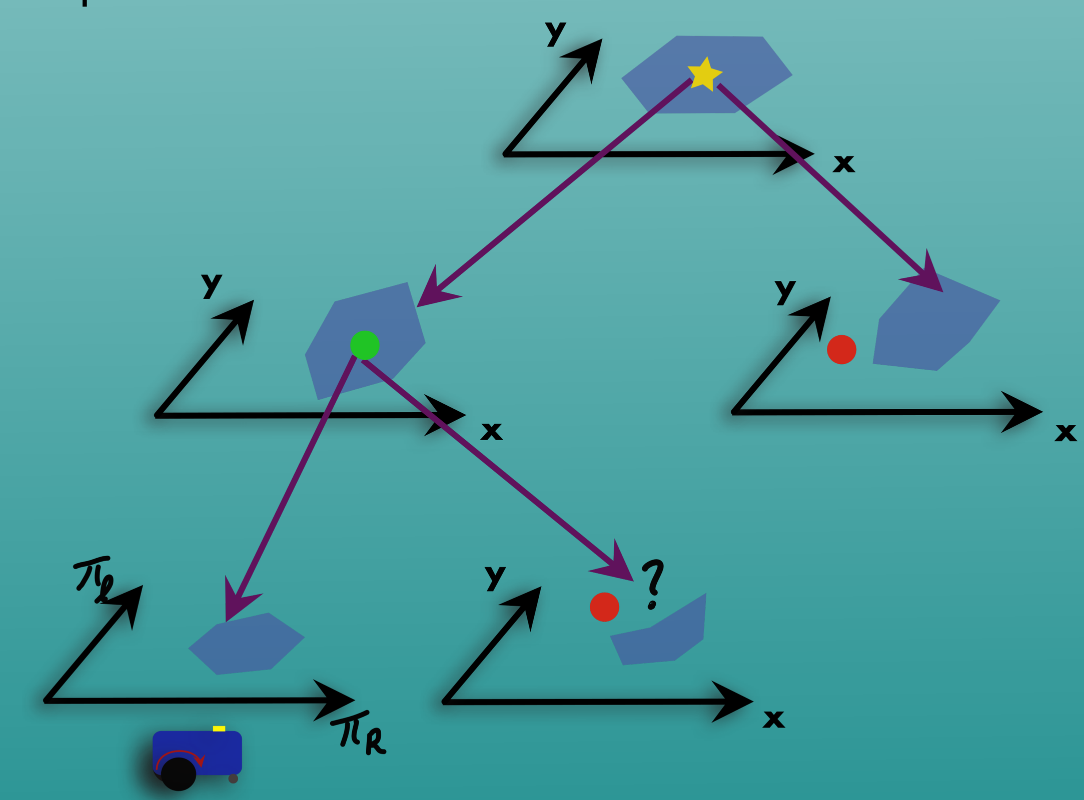
The learning procedure is guided by intrinsic motivation, i.e. we choose goals that lead us to explore regions with high interest of the state space (correspond to higher learning progress).

Using **Symbolic analysis:**

Current hierarchical learning approaches struggles with data-efficiency as the hierarchy grows, which hinder the continual learning at scale.
The use of set-based methods (e.g. abstract interpretation) could reduce the number of samples needed to learn models of affordances, with better handling of discontinuous hierarchies.
Inferring over sets better than inferring over points in the common sense, but we may need special abstract domains to serve our goal, especially for neural networks with ReLU activation functions.



Planning when using set-based methods could be improved over usual mapping, as the controllable regions of the state space will be intuitively the output set of the inverse model.



References:
[1] A Manoury, S. M. Nguyen, and C. Buche. CHIME: an adaptive hierarchical representation for continuous intrinsically motivated exploration. In IRC, 2019.
[2] T. Gehr, M. Mirman, D. Drachsler-Cohen, P. Tsankov, S. Chaudhuri, and M. T. Vechev. AI2: safety and robustness certification of neural networks with abstract interpretation. In SP, 2018.