In these problems, a robot must plan in a cluttered environment, reasoning about moving multiple objects in order to achieve a goal.

### Three inherent challenges:
1. Planner must search across an infinite dimensional belief space
2. Uncertainty in initial state, manipulator motion and physical interactions
3. Making and sustaining meaningful contact with objects

### Unobservable Monte Carlo Planning (UMCP)

Our insight is that by carefully selecting a goal informed default policy that generates actions with the goals of rearrangement planning and nonprehensile interaction in mind, we can extract useful trajectories from the planner to better guide the search.

The UMCP planner produces paths that exhibit higher probability of success compared to baseline state space planners.

Using contact actions (—) allows for finding better paths than using only basic actions (—) on both a low clutter scene (left) and a high clutter scene (right).

Use of goal informed default policies such as the planned (—) and learned (—) result in overall better paths compared to using a policy that randomly selects actions (—) for a low clutter scene (left). The planned default policy performs better than the learned and random default policies in a high clutter scene (right).

On simple scenes (top), the B-RRT (b=2.0) from (—) is able to find better paths quickly. The UMCP algorithm (—) is able to find better paths more quickly than the B-RRT (b=0.0) (—). On difficult scenes (bottom), the UMCP outperforms the B-RRT.