Although real-world dynamics are often sparse, most model-based RL still learns dense dynamics. In the real world, the next step value of each state variable often only depends on a few current state variables. But dense models depend on all variables and the action, making them vulnerable to spurious correlations.

**Method**

Given a high-level state space and action space, our method:
1. learns a causal dynamics model from transition data
2. splits state variables into three types:
   - controllable: can be affected by the action
   - action-relevant: can’t be affected by the action, but affect action’s results
   - action-irrelevant: all other variables
3. derives a state abstraction by ignoring action-irrelevant variables
4. uses the abstracted causal dynamics to learn (many) downstream tasks

In step 1, to determine if $s_i^{t+1} \rightarrow s_j^{t+1}$ between each state variable pair, we check if $s_i^t$ is needed to predict $s_j^{t+1}$.

$p(s_j^{t+1} | s_i^t, a_t) \neq p(s_j^{t+1} | s_j^t, a_t)$

In a synthesized and a table-top manipulation environment, our method learns the correct causal graphs. Sparse dynamics models not only generalize better than dense ones, but also enable a state abstraction that is task (reward)-independent.