

Learning from Interventions with Hierarchical Policies for Safe Learning

Jing Bi¹, Vikas Dhiman², Tianyou Xiao¹, Chenliang Xu¹ ¹{jbi5@ur., txiao3@u., chenliang.xu@}rochester.edu, ²vdhiman@ucsd.edu



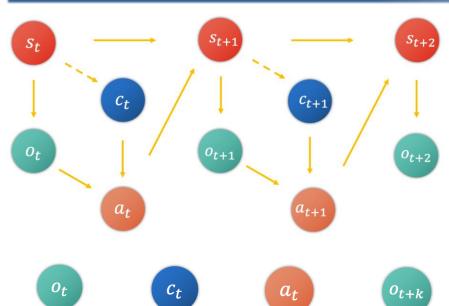
Motivation:

- Methods for solving compounding error often need to execute imperfect policy in the environment, which is infeasible in real world setting.
- The state-of-the-art Learning from Intervention fails to account for delay caused by the expert's reaction time and only learns short-term behavior.

Contributions:



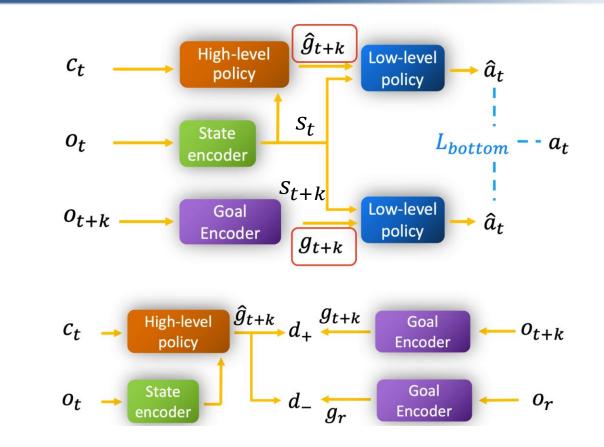
PROBLEM FORMULATION



An agent interacting with an environment in discrete time steps which is considered as a Goal-conditioned MDP

 o_t = observation at time-step t a_t = action based on o_t and c_t

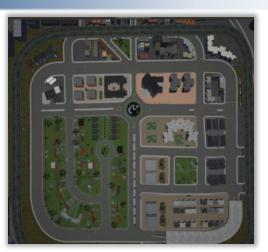
HIERARCHICAL POLICIES



The structure of hierarchical policy with triplet network

RESULT AND ANALYSIS



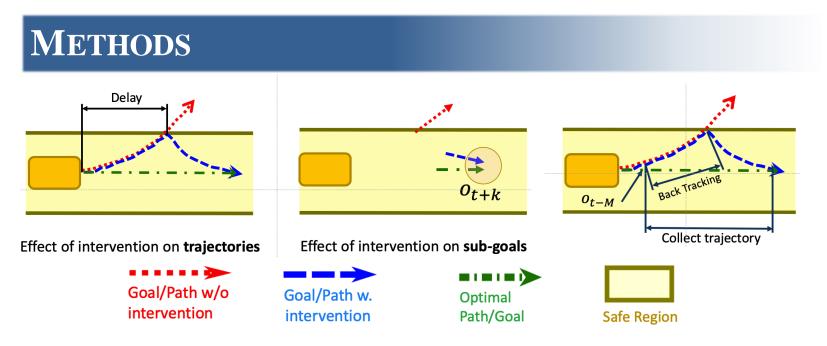






 c_t = command which indicates human intention o_{t+k} = future observation after k

time~steps



- Intervention with reaction caused a non-negligible difference between the intervened trajectory and the desired one.
- We formulate the intervention in terms of sub-goals to minimize this discrepancy --- The top-level policy to predict the right goal and the bottom policy will generate the correct actions that will bring the car to the goal



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Figure 1: Top view of the map in CARLA simulator and realworld environment where experiments were conducted.

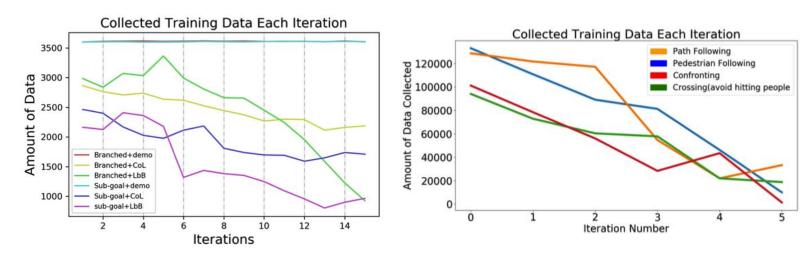


Figure 2: Comparison of the number of data-samples per iteration needed to train the various algorithms.

