Belief Regulated Dual Propagation Networks

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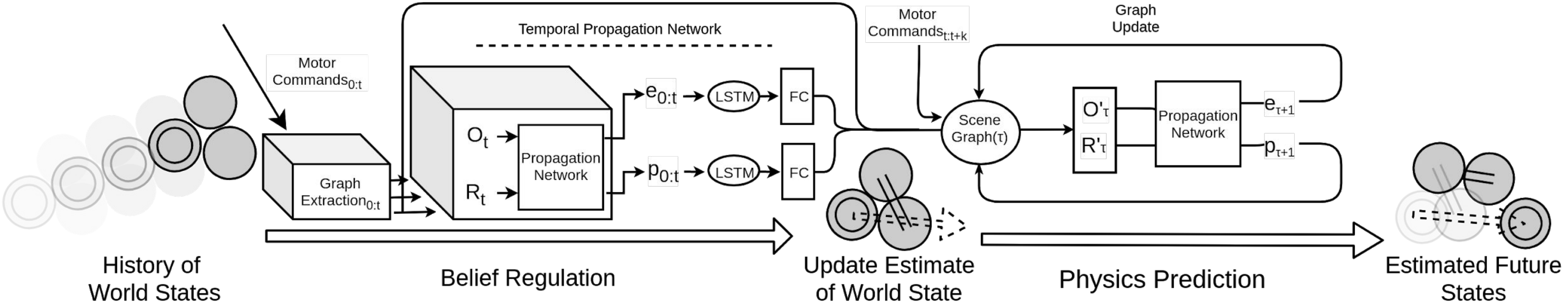
Summary

- In a table top scenario, we represented the scene as graph. We extended propagation network for joint type prediction. We used temporal data for joint relation prediction and current state for effect prediction.



Why graph neural network:

- Relational Inductive Bias
  - Object Centric Representation: Position Differences
  - Relation Centric Representation: Articulations.
  - Different objects and relations sharing representation.
  - Allows engineer to put prior knowledge(inductive bias) during graph creation: For contact relation, only create edges between close objects.

What is Propagation Network

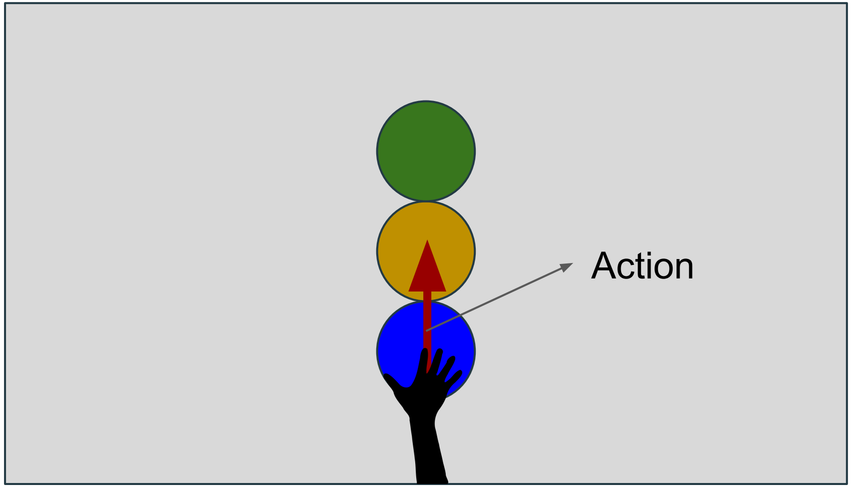
Encoding Part

- Relation Encoder: $$c^r_{k,t} = f^{enc}_R(r_{k,t}), \quad k = 1 \ldots N^r \tag{1}$$
- Object Encoder: $$c^o_{i,t} = f^{enc}_O(o_{i,t}), \quad i = 1 \ldots N^o \tag{2}$$

Propagation Part

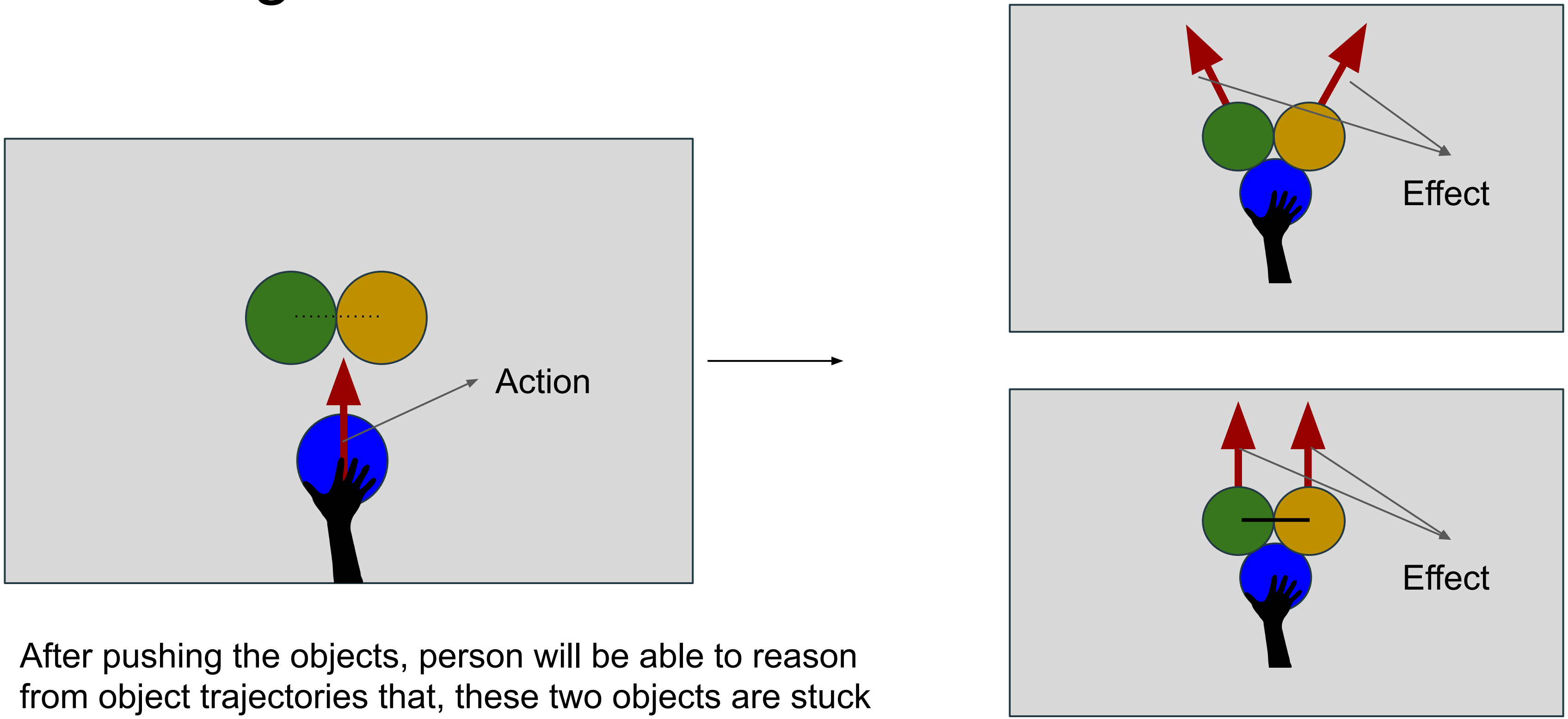
- Relation Propagator: $$e^l_{k,t} = f^l_R\left(c^r_{k,t}, p^{l-1}_{i,t}, p^{l-1}_{j,t}\right), \quad k = 1 \ldots N^r \tag{3}$$
- Object Propagator: $$p^l_{i,t} = f^l_O\left(c^o_{i,t}, p^{l-1}_{i,t}, \sum_{k \in \mathcal{N}_i} e^{l-1}_{k,t}\right), \quad i = 1 \ldots N^o \tag{4}$$

Why Use Propagation Networks:



Let's say we model pushing objects with other objects. In this case, if a person holds the blue object and push it towards yellow object, all three objects will move with propagated effects of blue object pushing yellow, and yellow pushing green.

Belief Regulation



After pushing the objects, person will be able to reason from object trajectories that, these two objects are stuck together or not. We propose that propagation network can be used for belief regulation.

Temporal Propagation Network

For long term belief regulation, our network should also consider previous timesteps.

Our main theoretical contribution in this paper is, we propose a temporal propagation network architecture that augments a propagation network with a recurrent neural network (RNN) unit to regulate beliefs regarding object and relation information over time.

$$r'_{k,t} = f_O^{blf}\left(e^L_{k,t}, r'_{k,t-1}\right), \quad k = 1 \dots N^r \tag{5}$$

$$o'_{i,t} = f_R^{blf}\left(p^L_{i,t}, o'_{i,t-1}\right), \quad i = 1 \dots N^o) \tag{6}$$

Setups

(a) Simulation (b) Real World (c) Sparse (d) Dense

Fig. 2: Robotic setup. Table top scenes used in (a) simulation and (b) real world experiments. (c)-(d) Initial configurations used for training and testing.

Results - Joint Type Prediction

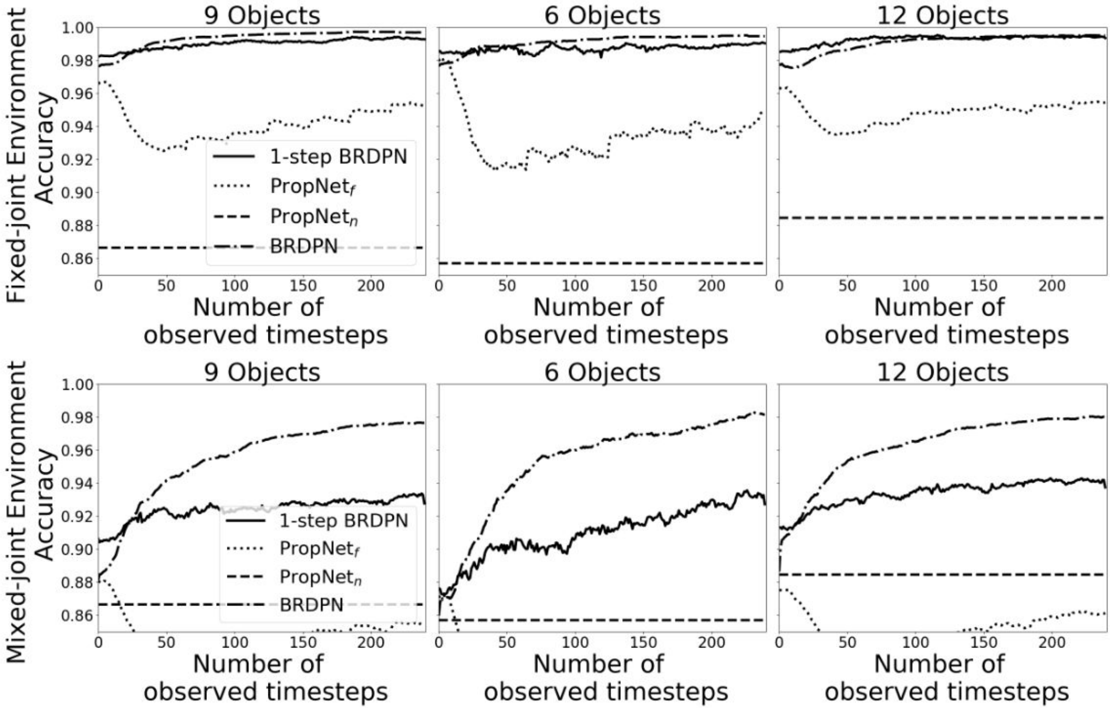
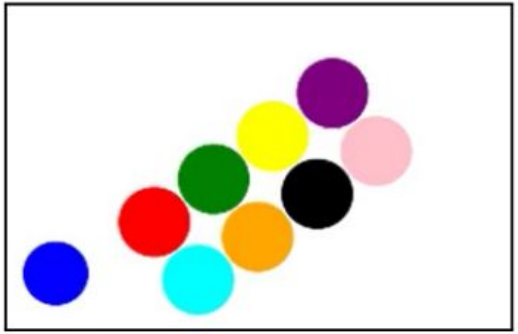
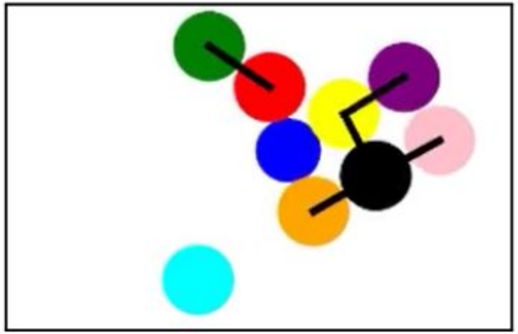


Fig. 4: Relation prediction accuracies (sparse configuration).

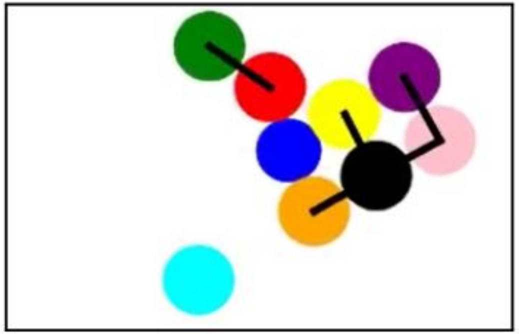
Relation Prediction - Ambiguity



(a) Initial Scene



(b) Predicted Relations



(c) Ground Truth Relations

BRDPN - Full System

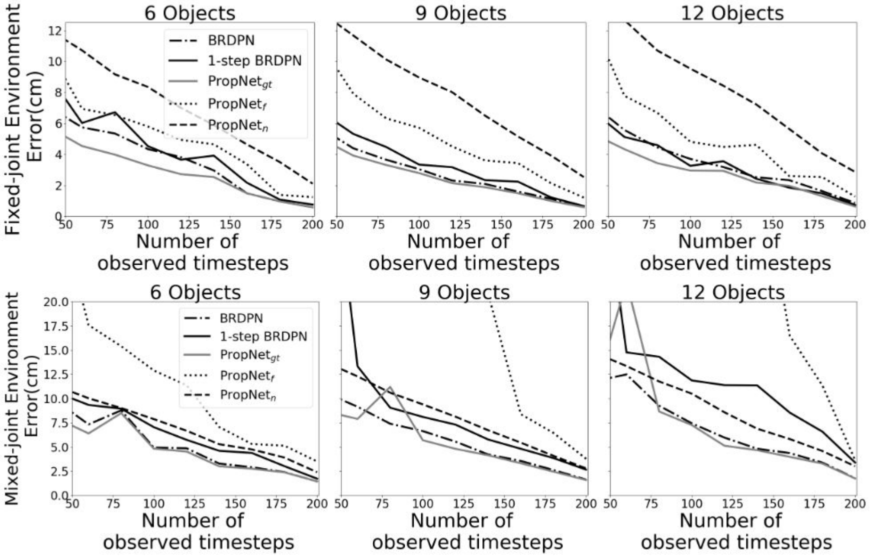


Fig. 6: Error of the BRDPN in sparse configuration.

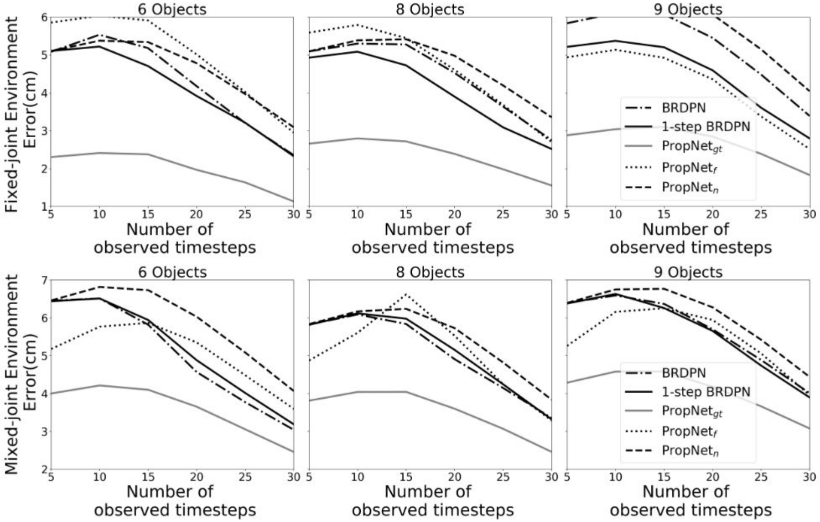


Fig. 7: Error of the BRDPN in dense configuration.

Results - Real World and Visualization