Generative Causal Representation Learning for Out-of-Distribution Motion Forecasting

Shayan Shirahmad Gale Bagi¹, Zahra Gharaeae², Oliver Schulte³, Mark Crowley¹

¹Department of Electrical and Computer Engineering, University of Waterloo, Waterloo, Canada
²Department of Systems Design Engineering, University of Waterloo, Waterloo, Canada
³School of Computing Science, Simon Fraser University, Burnaby, Canada

ABSTRACT

Conventional supervised learning methods typically assume i.i.d samples and are found to be sensitive to out-of-distribution (OOD) data. We propose Generative Causal Representation Learning (GCRL) which leverages causality to facilitate knowledge transfer under distribution shifts. First, we propose a novel causal model that explains the generative factors in motion forecasting datasets using features that are common across all environments and with features that are specific to each environment. Selection variables are used to determine which parts of the model can be directly transferred to a new environment without fine-tuning. Second, we propose an end-to-end variational learning paradigm to learn the causal mechanisms that generate observations from features. Experimental results on synthetic and real-world motion forecasting datasets show the robustness and effectiveness of our proposed method for knowledge transfer under zero-shot and low-shot settings.

PROBLEM DEFINITION

- **Given:**
  - 2D coordinates of agents in the observed $T_{obs}$ time steps
  - Training data with multiple environments.
- **Objectives:**
  - Predicting the states of agents in the next $T_{pred}$ time steps in a new environment.
- **Examples scenes from ETH-UCY dataset:**

![Image taken from (Amirian et al., 2020)](https://www.PosterPresentations.com)

PROPOSED METHOD

- **Endogenous variables:**
  - Past trajectories (X)
  - Future trajectories (Y)
  - Invariant features (Z)
  - Variant features (S)
- **Exogenous variables:**
  - Selection variable (E)
- **Examples:**
  - Invariant features are common across domains. These features can be associated with physical laws.
  - Variant features vary across domains and can be associated with the motion styles.
  - The selection variable acts as an identifier of an environment

![Image](https://www.PosterPresentations.com)

**METHOD**

<table>
<thead>
<tr>
<th>METHOD</th>
<th>ADE/FDE</th>
<th>ADE/FDE</th>
<th>ADE/FDE</th>
<th>ADE/FDE</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>BASELINE (Huang et al., 2019)</strong></td>
<td>$0.86/1.37$</td>
<td>$2.15/2.80$</td>
<td>$2.64/4.44$</td>
<td>$2.68/4.48$</td>
</tr>
<tr>
<td><strong>COUNTERAFTUAL (Chen et al., 2021)</strong></td>
<td>$0.80/1.59$</td>
<td>$1.62/2.68$</td>
<td>$2.32/3.90$</td>
<td>$2.68/4.52$</td>
</tr>
<tr>
<td><strong>INVARIANT latent</strong></td>
<td>$0.94/1.65$</td>
<td>$1.04/1.76$</td>
<td>$1.52/2.55$</td>
<td>$1.96/3.35$</td>
</tr>
<tr>
<td><strong>INVARIANT latent</strong></td>
<td>$0.91/1.67$</td>
<td>$0.99/1.87$</td>
<td>$1.18/2.20$</td>
<td>$1.27/2.33$</td>
</tr>
<tr>
<td><strong>GCRF (OURS)</strong></td>
<td>$0.98/1.79$</td>
<td>$1.00/1.83$</td>
<td>$1.20/1.99$</td>
<td>$1.56/2.58$</td>
</tr>
</tbody>
</table>

**RESULTS**

- Table: our method is robust against observation noise while performing comparably with other motion forecasting models.
- Our proposed method also learns to reconstruct inputs: eliminates the effect of noise by reconstructing uncorrupted inputs.
- **Figure:** GCRL adapts to the new environment faster than IM (Liu et al., 2022)
  - More robust to OOD-Extra shifts.
  - GCRL improves the ADE by 34.3% from IM on average.

![Diagram](https://www.PosterPresentations.com)

**CONCLUSIONS**

We propose a method that leverages causality to learn meaningful features that can increase the robustness and transferability of deep learning models. In presence of spurious correlation, we demonstrated the robustness of our method while other human trajectory prediction models performed poorly compared to our method. Furthermore, our augmented causal model was able to enhance the transferability in a zero-shot and low-shot settings. It can be concluded from our results that incorporating causality in deep learning is a promising research direction towards robustness and explainability of deep learning models.

REFERENCES


CONTACT

If you have any questions/suggestions, please get in touch!
Shayan: sshirahm@uwaterloo.ca
Lab: https://markcrowley.ca/