Accounting for the Sequential Nature of States to Learn Features for Reinforcement Learning

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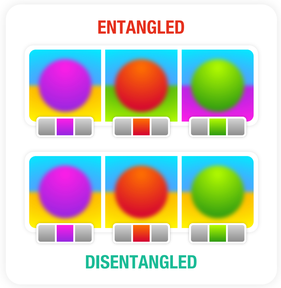
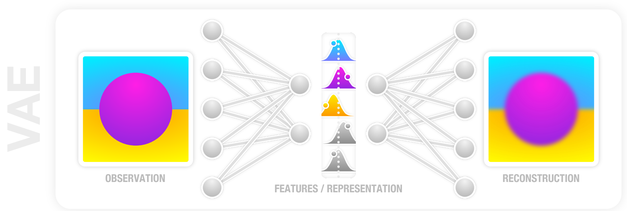
We use sequential states to learn better features for downstream tasks when we cannot rely on overlap in data

Introduction

- Variational Auto-Encoders (VAEs) learn **disentangled** representations from data, which are useful features for downstream Reinforcement Learning (RL) tasks.
- VAEs may fail and produce **entangled** representations if data does not overlap eg. Chess piece on a chess board.
- Can we fix this by using the sequential nature of RL states?

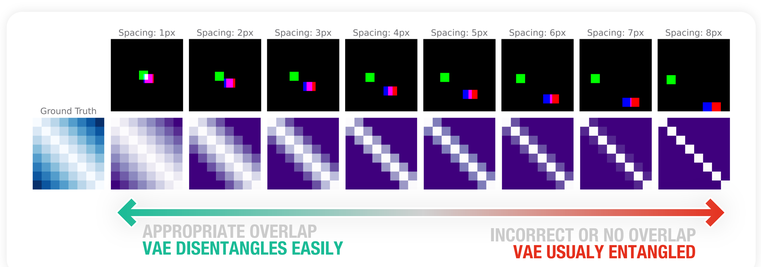




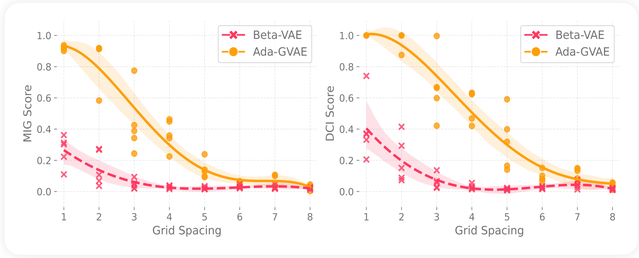
VAEs Perceive Overlap In Data

VAEs perceive distances between observations based on the chosen reconstruction loss.

- We design a simple 8x8 gridworld domain with adjustable spacing of x and y ground-truth factors to test this.



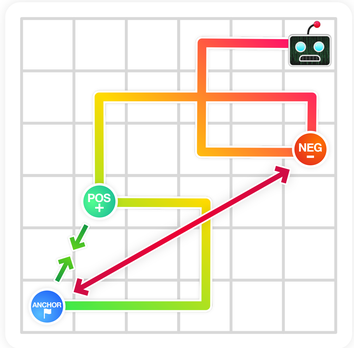
- Train VAEs over gridworld datasets with varying spacing. More overlap in the data gives better disentanglement.



Using Sequential States

How can we remedy this problem for environments that do not contain sufficient overlap in data?

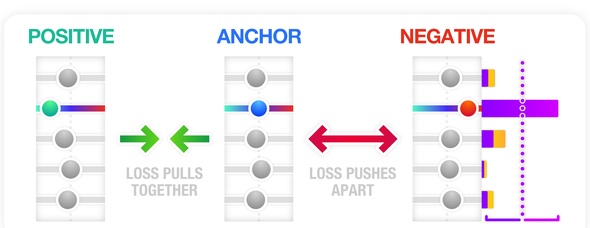
- Use an RL replay buffer and make the assumption that: *states further in time on average have more differing ground-truth factors*.
- Allows us to construct triplets for metric learning, where distances between representations of **anchor-positive** observations should be less than those of the **anchor-negatives**.



Adaptive Triplet Loss

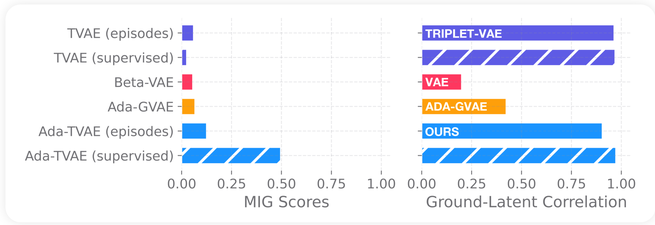
Standard triplet loss does not encourage disentanglement. So we instead encourage differences to be encoded in a subset of latent variables.

- We **weight** elements of the **anchor-negative** term less if their **absolute differences** are less than half way between the **min and the max**.



Our approach outperforms **standard triplet** and **VAE baselines**, when trained over our non-overlapping gridworld domain.

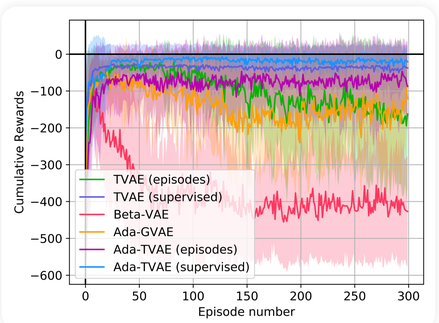
- We compare ground-truth constructed triplets versus those constructed from the replay buffer.



Downstream Tasks

We use the previously trained VAEs to extract features used to make decisions by a downstream reinforcement learning agent

- The agent is tasked to move from one corner to another in the non-overlapping gridworld environment.
- Our adaptive triplet VAEs perform best. ● ●



Conclusion

Using sequential state information can improve the features learnt in problematic environments where data is non-overlapping and traditional methods fail

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