Learning Agent Representations for Ice Hockey

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Player Representation via Generation

 Contextualized representation: Apply latent variables z_t as a representation of game context:

$$p(pl_t|\mathbf{s}_t, \mathbf{a}_t, \mathbf{r}_t) = \int p(pl_t|\mathbf{z}_t) p(\mathbf{z}_t|\mathbf{s}_t, \mathbf{a}_t, \mathbf{r}_t) d\mathbf{z}_t$$

to Learn a *context-aware prior* $p(\mathbf{z}_t | \mathbf{s}_t, \mathbf{a}_t, \mathbf{r}_t)$.

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• After observing the acting player pl_t , we learn an approximate posterior $q(\mathbf{z}_t | \mathbf{s}_t, \mathbf{a}_t, \mathbf{r}_t, pl_t)$ as a contextualized player representation:

$$p(pl_t|\mathbf{s}_t, \mathbf{a}_t, \mathbf{r}_t) \approx \int p(pl_t|\mathbf{z}_t)q(\mathbf{z}_t|\mathbf{s}_t, \mathbf{a}_t, \mathbf{r}_t, pl_t) \mathrm{d}\mathbf{z}_t$$

Model Structure

Variational Recurrent Ladder Agent Encoder (VaRLEA)

- Build a *contextualized* Ladder VAE at RNN cell
 - 1. Ladder latent variables $(z_{s,t}, z_{a,t}, z_{r,t})$ for maintaining the *causal dependency* $s \rightarrow a \rightarrow r$.
 - **2. Generation**: Estimate *contextualized prior*.
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- Shrinkage Effect:
 - Allow information to transfer between Player observations.
 - 2. Shrinkage estimator prevents overfitting



Conclusion

The take-home message:

- The VAE ELBo loss is an effective *shrinkage estimator* for large multi-agent action datasets with
 - **1**. Diversity (many different agents).
 - 2. Sparsity (some agents with limited observations).
- Modeling player information with player representation improves the performance of downstream applications.

