Diverse Generation for Multi-agent Sports Games

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Motivation

Task: Given past trajectories, forecast possible future scenarios

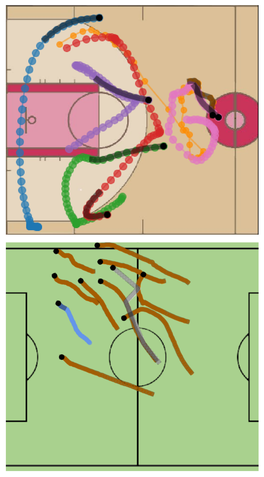
- Trajectories of multi-agent sports games, *e.g.* basketball

Challenges:

- Diverse generation
- Consistent representation
- Temporal modeling

Contributions:

- Propose Graph Variational RNN (GVRNN)
- Permutation equivariant representation with graph nets
- Sampling capability utilizing variational autoencoder (VAE)
- Temporal modeling via recurrent neural network (RNN)



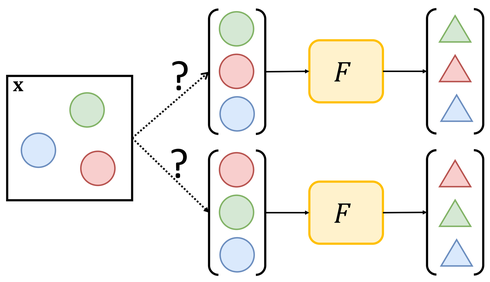
Introduction

Problem Formulation:

Given a dataset $\mathcal{D} = \{\mathbf{x}\}$, model $p_\theta(\mathbf{x})$

- Game segment $\mathbf{x} = \{\mathbf{x}_1, \dots, \mathbf{x}_K\}$, where K = # agents
- Agent trajectory $\mathbf{x}_k = (\mathbf{x}_k^1, \dots, \mathbf{x}_k^T)$, where T = # time steps
- Agent position $\mathbf{x}_k^t \in \mathbb{R}^2$ denotes in-game 2D location

Consistent Representation (Permutation Equivariant):



- Vector representation of $\mathbf{x}$
- $F_\theta(\pi\mathbf{x}) = \pi F_\theta(\mathbf{x})$, where π is a permutation matrix
- General deep nets are <u>not</u> equivariant

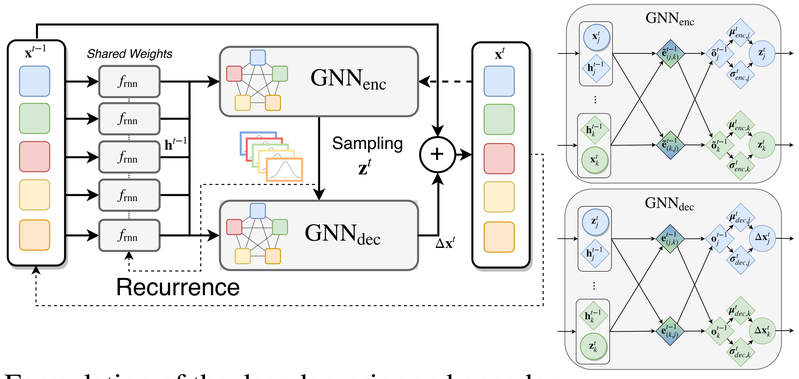
Our Approach

Variational RNN: VRNNs are trained by maximizing the evidence lower bound:

$$\sum_{\mathbf{x}\in\mathcal{D}} \sum_t \mathbb{E}_{q_\phi(\mathbf{z}^t|\mathbf{x}^{\le t}, \mathbf{z}^{<t})} \Big[\log p_\theta(\mathbf{x}^t|\mathbf{x}^{<t}, \mathbf{z}^{\le t}) - D_{\mathrm{KL}}(q_\phi(\mathbf{z}^t|\mathbf{x}^{\le t}, \mathbf{z}^{<t}) || p_\theta(\mathbf{z}^t|\mathbf{x}^{<t}, \mathbf{z}^{<t})) \Big]$$

where $p_\theta(\mathbf{x}^t|\mathbf{x}^{<t}, \mathbf{z}^{\le t})$, $p_\theta(\mathbf{z}^t|\mathbf{x}^{<t}, \mathbf{z}^{<t}))$, and $q_\phi(\mathbf{z}^t|\mathbf{x}^{\le t}, \mathbf{z}^{<t})$ each corresponds to the decoder, prior and encoder.

Graph Variational RNN: Through parameter sharing and aggregation over all edges, GNN achieves permutation equivariance:



Formulation of the decoder, prior and encoder:

$$p_\theta(\mathbf{z}^t|\mathbf{x}^{<t}, \mathbf{z}^{<t}) = \prod_k \mathcal{N}(\mathbf{z}^t|\boldsymbol{\mu}^t_{\text{pri},k}, (\boldsymbol{\sigma}^t_{\text{pri},k})^2),$$

$$q_\phi(\mathbf{z}^t|\mathbf{x}^{\le t}, \mathbf{z}^{<t}) = \prod_k \mathcal{N}(\mathbf{z}^t|\boldsymbol{\mu}^t_{\text{enc},k}, (\boldsymbol{\sigma}^t_{\text{enc},k})^2),$$

$$p_\theta(\mathbf{x}^t|\mathbf{x}^{<t}, \mathbf{z}^{\le t}) = \prod_k \mathcal{N}(\mathbf{x}^t|\boldsymbol{\mu}^t_{\text{dec},k}, (\boldsymbol{\sigma}^t_{\text{dec},k})^2),$$

$$h^t_k = f_{\text{rnn}}(\mathbf{x}^t_k, \mathbf{z}^t_k, h^{t-1}_k),$$

where

$$[\boldsymbol{\mu}^t_{\text{pri},1:K}, \boldsymbol{\sigma}^t_{\text{pri},1:K}] = \text{GNN}_{\text{pri}}(h^{t-1}_{1:K}),$$

$$[\boldsymbol{\mu}^t_{\text{enc},1:K}, \boldsymbol{\sigma}^t_{\text{enc},1:K}] = \text{GNN}_{\text{enc}}([\mathbf{x}^t_{1:K}, h^{t-1}_{1:K}]),$$

$$[\boldsymbol{\mu}^t_{\text{dec},1:K}, \boldsymbol{\sigma}^t_{\text{dec},1:K}] = \text{GNN}_{\text{dec}}([\mathbf{z}^t_{1:K}, h^{t-1}_{1:K}]).$$

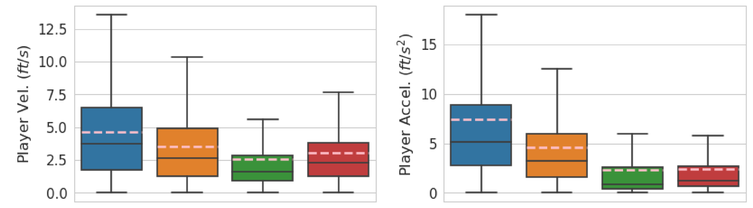
Results

Quantitative Results:

Approach	Equiv.	Relation	L_2 (Best)	Cond. L_2 (Best)
RNN	✗	✓	11.46 ± .05	12.04 ± .04
VRNN	✗	✓	09.02 ± .02	09.79 ± .04
GVRNNT-Diag	✓	✗	08.87 ± .02	10.63 ± .04
GVRNNT-Full	✓	✓	**08.26** ± .02	**07.88** ± .03

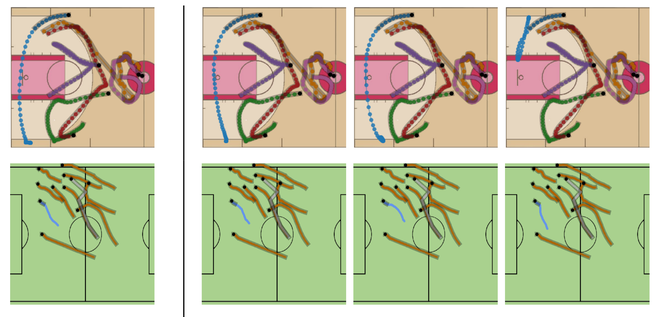
Quantitative comparisons on basketball dataset reported in ft

- L_2 (Best): L_2-error over all agents, the best out of 10
- Cond. L_2 (Best): Generation of the ball's trajectory conditioned on players'

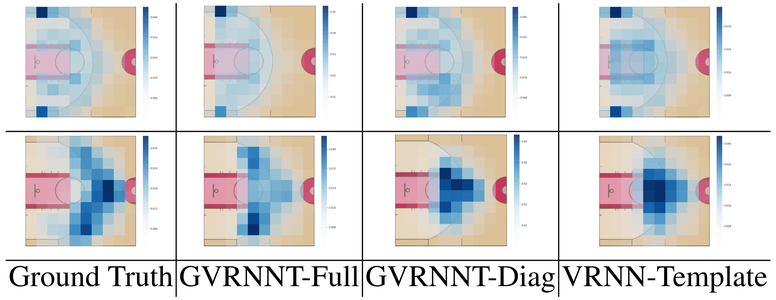


Ground Truth, GVRNNT-Full, GVRNNT-Diag, VRNN

Qualitative Results:



Ground-Truth Possible futures for the blue player



Ground Truth | GVRNNT-Full | GVRNNT-Diag | VRNN-Template