MG-GAN: A Multi-Generator Model Preventing Out-of-Distribution Samples in Pedestrian Trajectory Prediction

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Website Code Paper

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TL;DR

Problem

Single generator methods are **incapable of learning a multimodal distribution** and predict **out-of-distribution samples**.

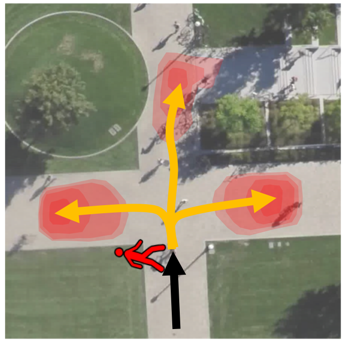
➔ Predicting out-of-distribution (OOD) samples harming real-world applications

Solution

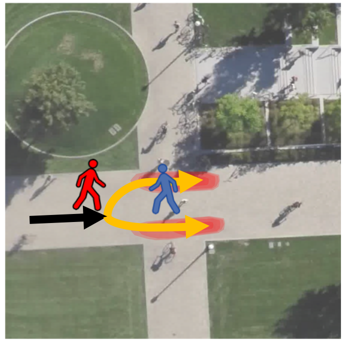
Multi-generator method with generators specializing in **different modes. Path Mode Network** the generators based on the observations in the scene.

Motivation

Distribution of future trajectories of pedestrians is highly multi-modal and often has **disconnected support**

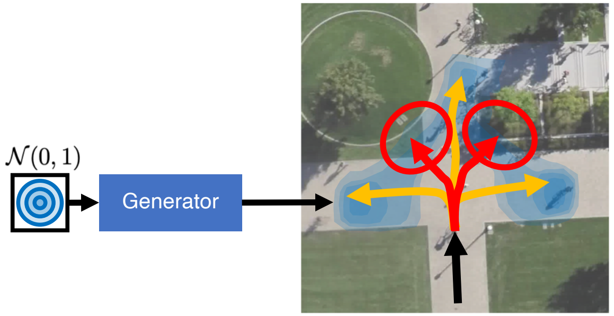


Spatial Multimodality



Social Multimodality

Single generator GANs transform **a continuous latent space** with a **continuous function** ϟ The support of the output is always connected

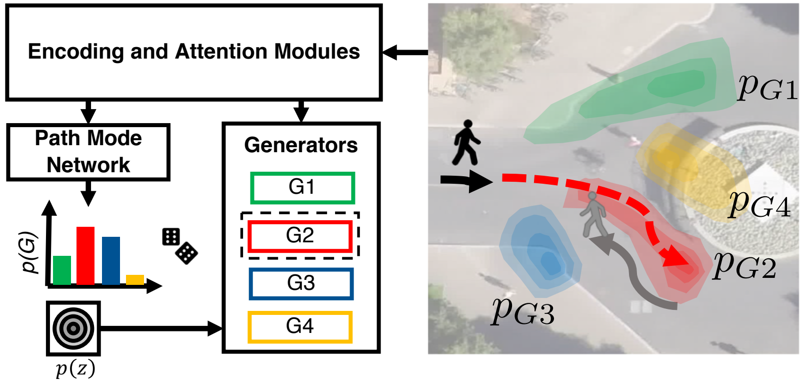


ϟ Out-of-distribution samples

Method

Model

- Learn **multiple generators** focusing on individual modes
- Train **Path Mode Network** to co-ordinate individual generators



Alternating Training Scheme

1. **PM-Network update**
   - Compute **responsibilities** of generators by compare predictions of each generator with ground-truth sample
   - **Minimize cross-entropy** between target and PM-Net output
2. **Generator update**
   - Obtain PM Net distribution and sample generators
   - Perform **regular GAN update** with sampled generators

Evaluation

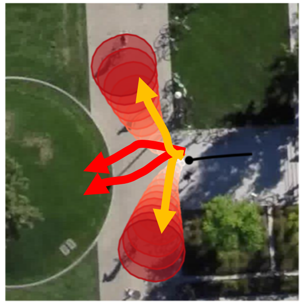
ϟ **ADE** and **FDE** is not sufficient to evaluate the quality of samples

Evaluating out-of-distribution samples is possible with [Kynkäänniemi, 19]

Precision: Measures quality of samples
Recall: Measures coverage of modes

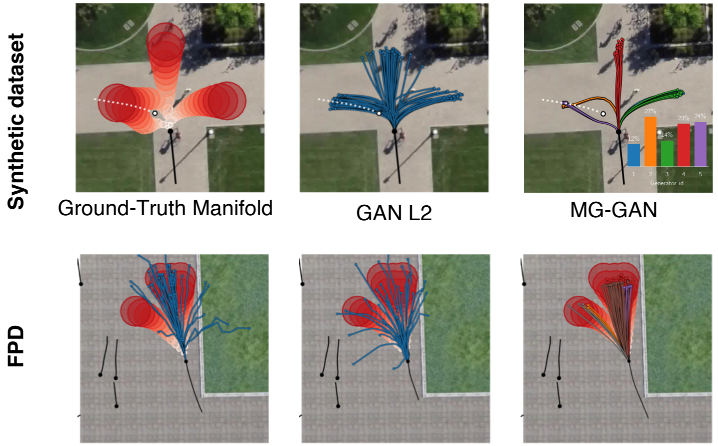
Computation requires access to multiple ground-truth samples, thus consider

- Synthetic dataset
- Forking paths dataset (FPD) [Liang 2020]



Results

Qualitative results



Ground-Truth Manifold | GAN L2 | MG-GAN

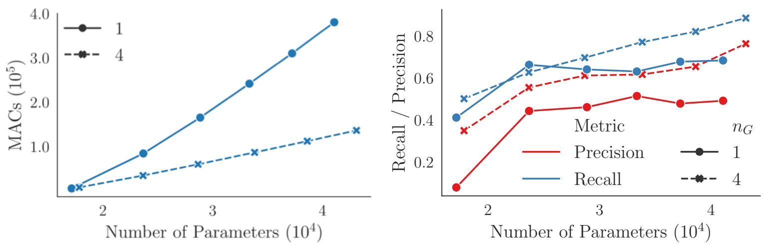
PECNet [Mangalam, 20] | Trajectron++ [Salzmann, 20] | MG-GAN (ours)

Quantitative results

FPD results

	ADE ↓	FDE ↓	Precision ↑	Recall ↑	F1 ↑
GAN+L2	28.81	58.37	0.55	0.87	0.67
PECNet	**13.14**	**24.55**	0.46	0.95	0.62
Trajectron++	13.15	32.00	0.38	**0.96**	0.54
MG-GAN (Ours)	22.09	46.38	**0.71**	0.89	**0.79**

➔ Significantly **higher precision indicating less OOD samples**!



➔ Multiple generators **perform better** & require **less computation** with same number of total parameters!