WALLENBERG AI, AUTONOMOUS SYSTEMS AND SOFTWARE PROGRAM

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Context-free Self-Conditioned GAN for Trajectory Forecasting

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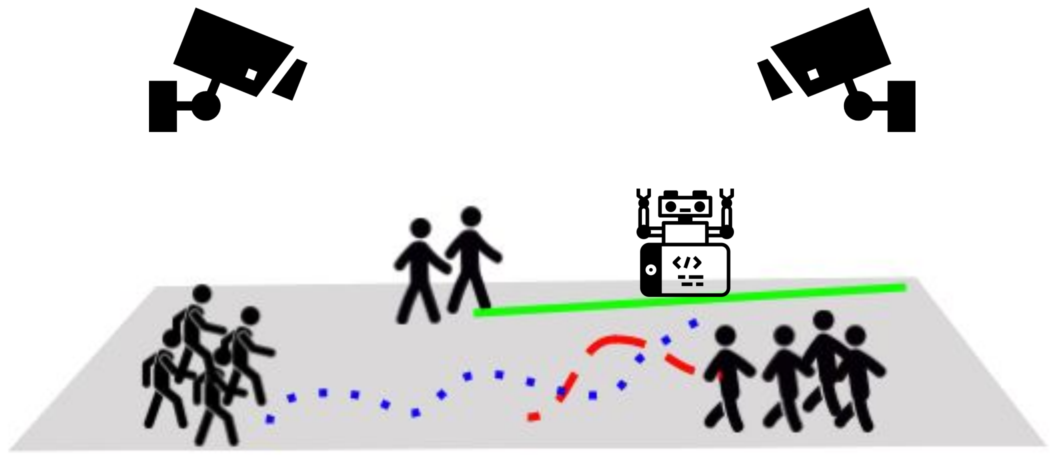
Motivation

- Learn different behaviors from trajectories
- Surveillance systems, autonomous vehicles, and service robots
- Proactive systems by perceiving behaviors
- Include behaviors in the trajectory forecasting task



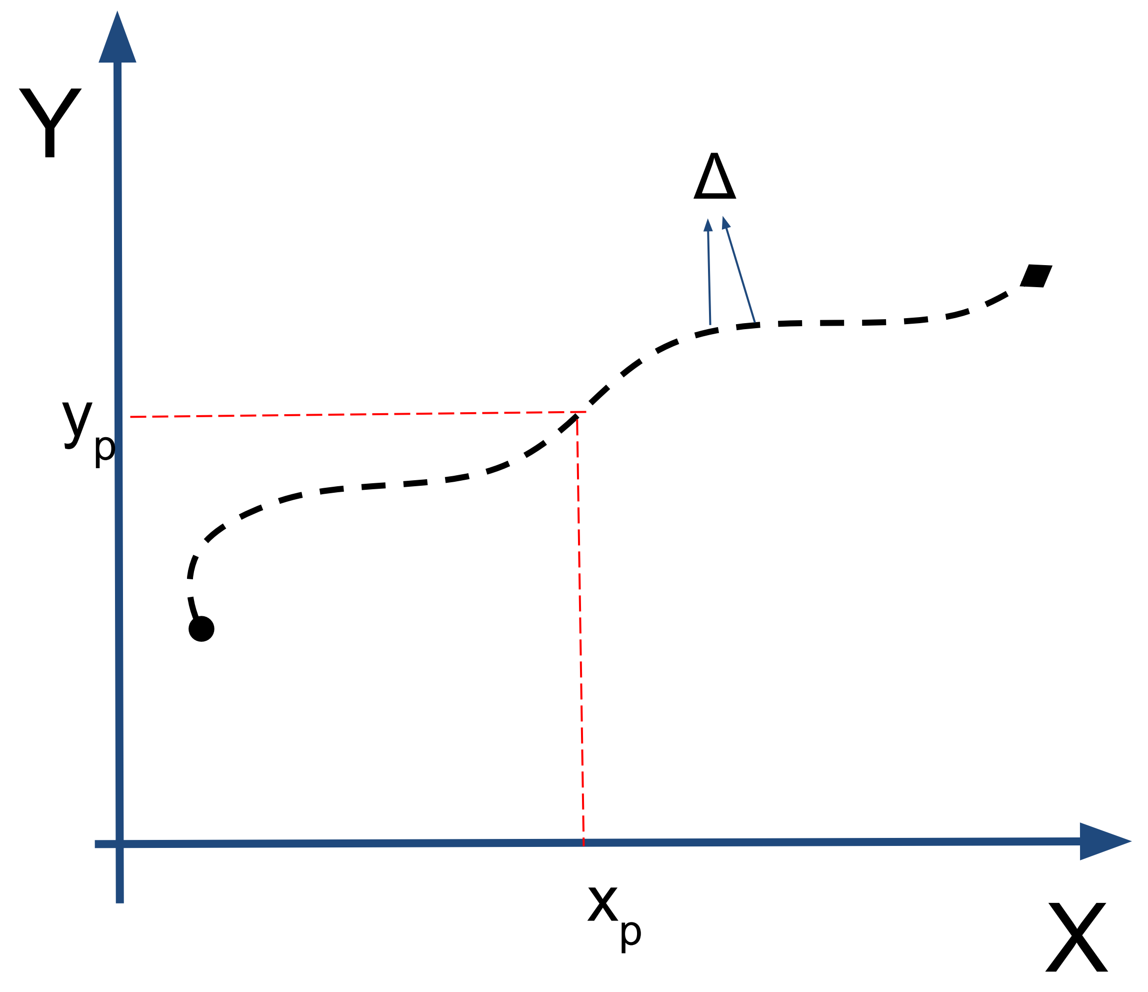
Problem Definition

Spatio-temporal data:

- $T_j=\{(\Delta x_1, \Delta y_1), \ldots (\Delta x_n, \Delta y_n)\}$

Trajectory forecasting:

- $\Delta X_j=\{(\Delta x_1, \Delta y_1), \ldots (\Delta x_p, \Delta y_p)\}$
- $\Delta Y_j=\{(\Delta x_{p+1}, \Delta y_{p+1}), \ldots (\Delta x_n, \Delta y_n)\}$?



Contributions

1. Adapt self-conditioned GAN (used for image generation) to the trajectory generation task *[Liu et. al ‘20]*

2. Attenuate *mode-collapse* via soft assumptions drawn from self-conditioned GAN

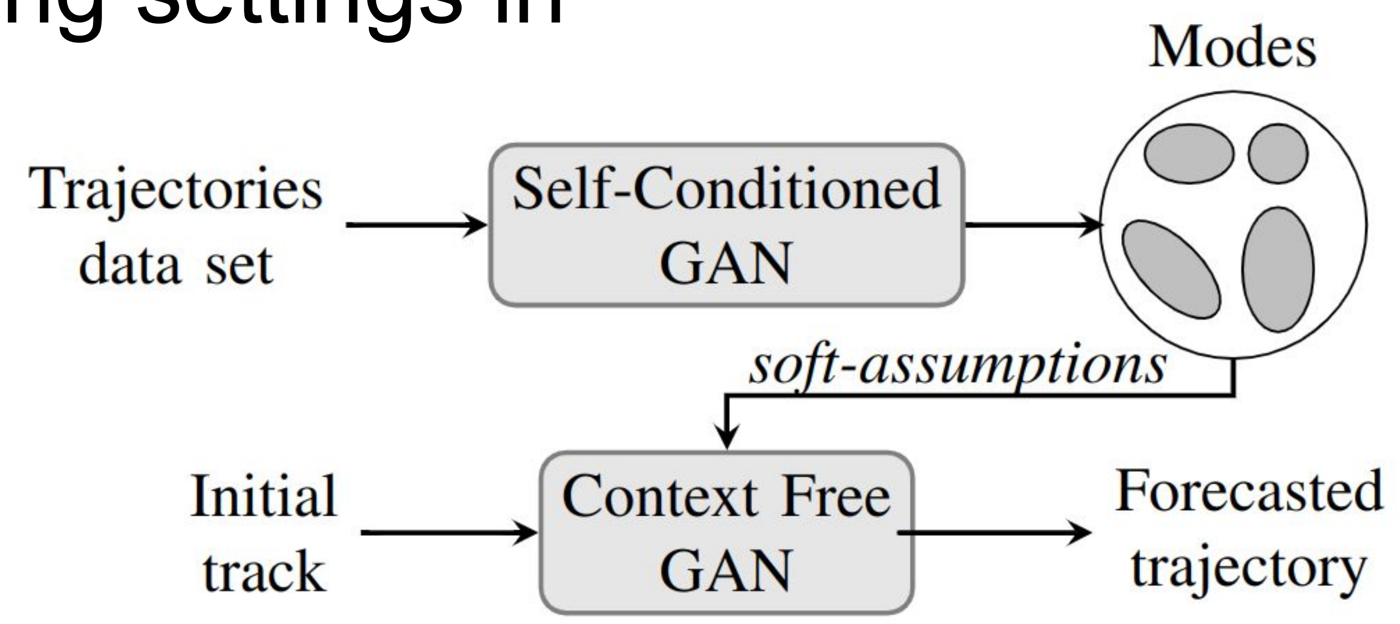
3. Three training settings that improve trajectory forecasting

Method

1. Identify meaningful modes via Self-conditioned GAN

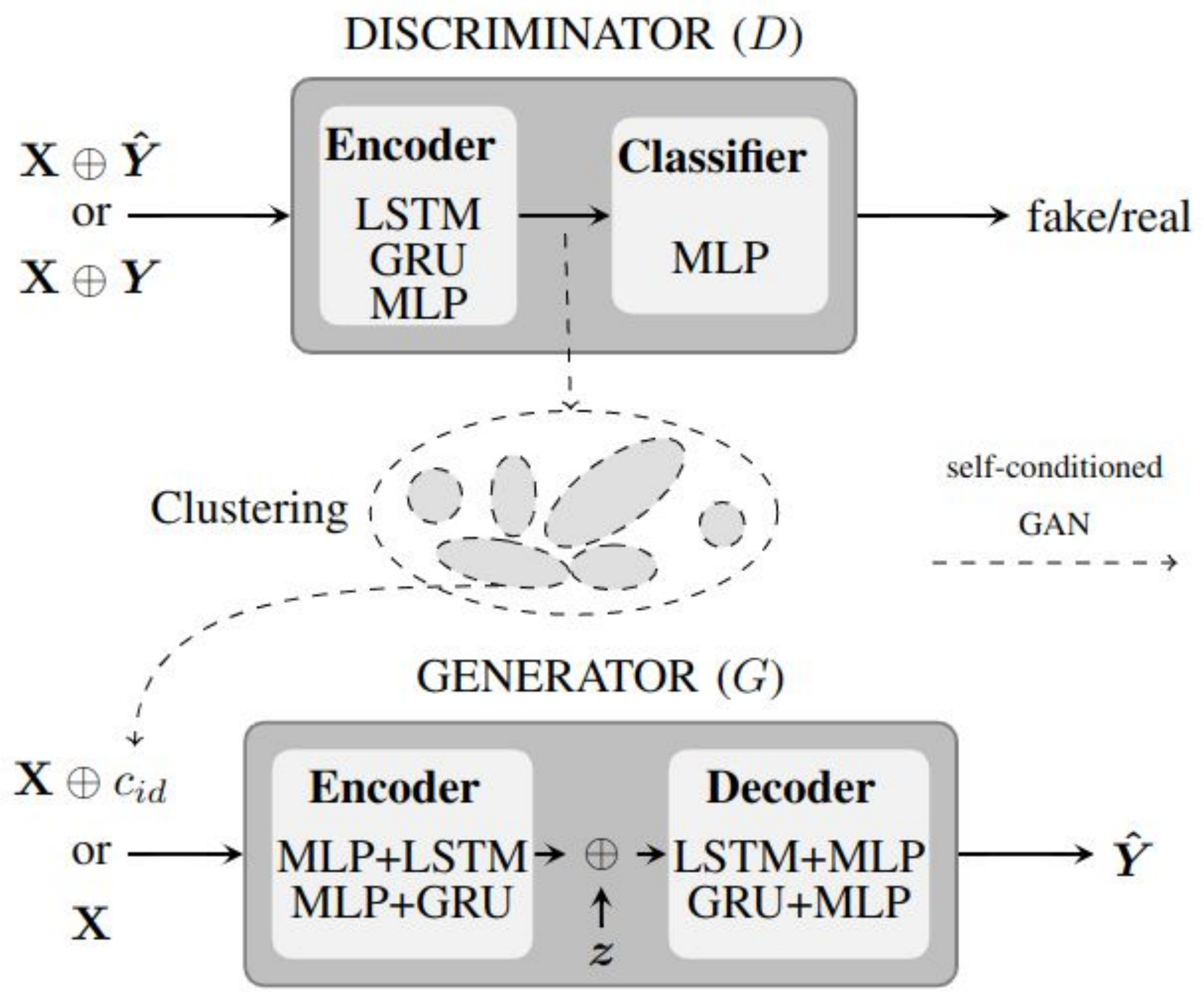
2. Use them to define soft-assumptions

3. Apply those soft-assumptions via training settings in a CF-GAN



Self-conditioned GAN

- Clusters in the discriminator's feature space (updated throughout the training)
- Self-supervised classes (generator conditioned on clusters' *ids*)
- Embed information provided by this clustering space into the trajectory generation task



Soft-assumptions based on Self-conditioned GAN

Metrics to assess the quality of the generation:

ADE: RMSE($\hat{Y}_j, Y_j$) **FDE:** d([($\hat{x}_n$, $\hat{y}_n$), (x_n, y_n)])

- Quality of the generation of clusters of trajectories (via ADE and FDE)
- Intra-cluster results define the **most challenging** groups of future trajectories
- Clustering space distribution defines the **representativeness** of unsupervised groups of trajectories from the input data

Proposed training settings

- Common generator's loss function given by the sum of:

$$\mathrm{MSE}(\boldsymbol{Y}, \hat{\boldsymbol{Y}}) = \frac{1}{n}\sum_{j}^{p} \min \|\boldsymbol{y_j} - \hat{\boldsymbol{y}}_{\boldsymbol{j}}\|_2, \quad L_{Adv} = \frac{1}{2}\mathbb{E}[(D(\boldsymbol{X}, \boldsymbol{Y}) - 1)^2] + \frac{1}{2}\mathbb{E}[D(\boldsymbol{X}, \hat{\boldsymbol{Y}})^2]$$

- **(1)** Penalize MSE (wL2) and **(2)** weighted batch sampler (wB) given by:

$$\Lambda_i = \lambda_{ADE} \frac{ADE_i}{ADE_{\max}} + \lambda_{FDE} \frac{FDE_i}{FDE_{\max}} + \lambda_D \frac{\#_i}{\#_{\mathrm{T}}}$$

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Experiments

THÖR *[Rudenko et. al '19]*

- 8-time steps observation (3.2s) 12-time steps prediction (4.8s) *[Kothari et. al '21]*
- task-driven roles: 5 or 6 *visitors*, 2 *workers*, and 1 *inspector*

Experiments

Argoverse *[Chang ‘19]*

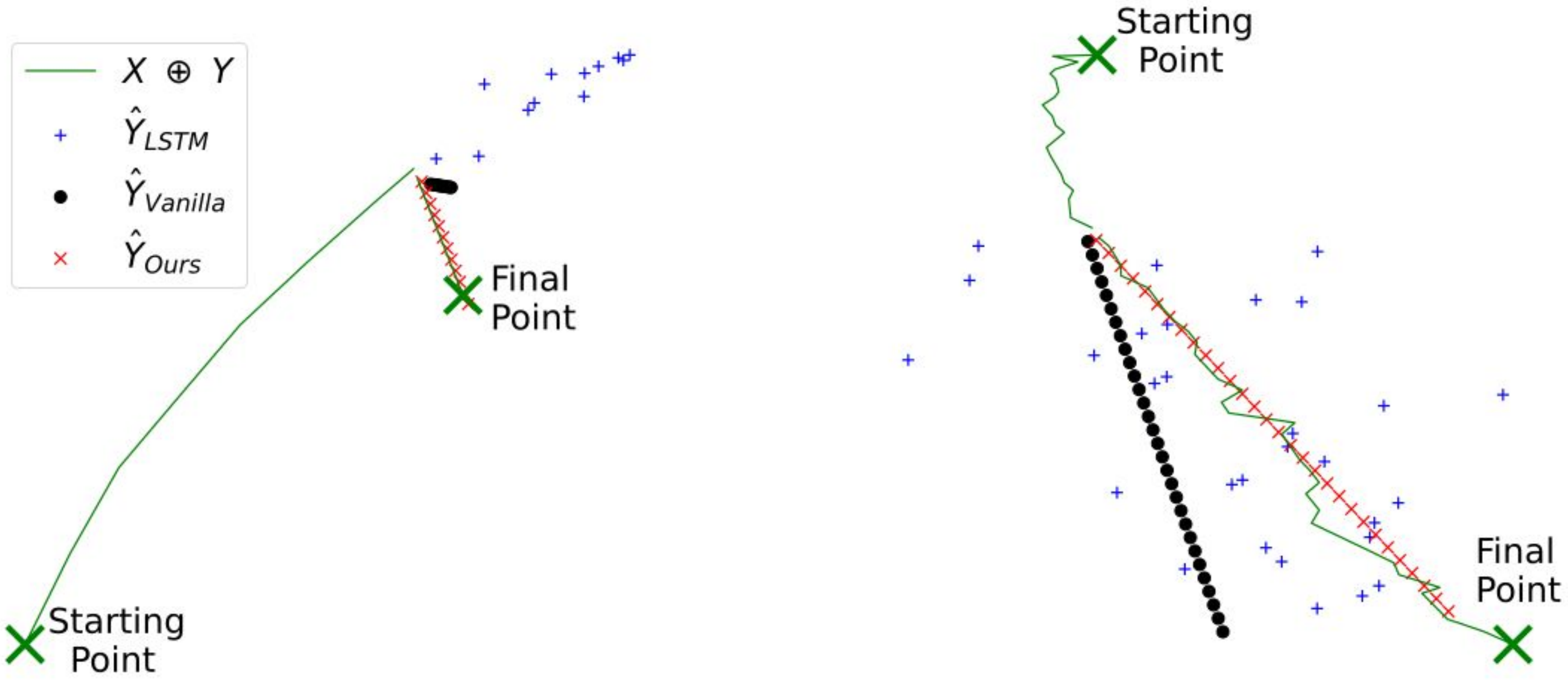
- 20-time steps observation (2s) 30-time steps prediction (3s)
- supervised classes: autonomous vehicles (*av*), regular vehicles (*agents*), other road agents (*others*)
- randomly sampled 5726, 2100, 1678 for training, validation and test sets, respectively *[Chandra et.al ‘20]*
- training set: 2600 from *av*, 2600 from *agents* and 526 from *others*

Experiments

INTRA-CLASSES ADE/FDE METRICS (IN METERS) IN THE TEST SETS.

		Baselines		Ours		
Data set	Labels (# samples)	LSTM [22]	CF VAN GAN [14]	CF VAN GAN + wL2	CF VAN GAN + wB	CF VAN GAN +wL2 + wB
THÖR	*workers* (413)	0.695 1.064	0.642 ± 0.006 1.033 ± 0.005	0.629 ± 0.005 1.009 ± 0.014	0.644 ± 0.012 1.044 ± 0.028	$\mathbf{0.625 \pm 0.009}$ $\mathbf{1.006 \pm 0.019}$
	visitors (1379)	0.664 1.139	0.660 ± 0.001 $\mathbf{1.105 \pm 0.090}$	$\mathbf{0.657 \pm 0.003}$ 1.107 ± 0.007	0.668 ± 0.005 1.124 ± 0.018	0.657 ± 0.003 1.113 ± 0.013
	inspector (260)	0.796 1.582	0.735 ± 0.007 1.474 ± 0.019	0.736 ± 0.008 $\mathbf{1.473 \pm 0.013}$	$\mathbf{0.729 \pm 0.013}$ 1.479 ± 0.049	0.734 ± 0.003 1.476 ± 0.015
Argoverse	*others* (526)	1.864 3.029	1.815 ± 0.031 2.969 ± 0.034	1.799 ± 0.007 2.944 ± 0.022	$\mathbf{1.789 \pm 0.012}$ 2.927 ± 0.020	1.801 ± 0.027 $\mathbf{2.919 \pm 0.032}$
	av (2600)	1.512 2.278	$\mathbf{1.467 \pm 0.007}$ $\mathbf{2.269 \pm 0.023}$	1.482 ± 0.009 2.292 ± 0.010	1.480 ± 0.003 2.282 ± 0.006	1.493 ± 0.010 2.298 ± 0.028
	agent (2600)	2.371 4.690	$\mathbf{2.349 \pm 0.012}$ $\mathbf{4.654 \pm 0.016}$	2.362 ± 0.013 4.700 ± 0.029	2.368 ± 0.020 4.721 ± 0.044	2.371 ± 0.012 4.724 ± 0.027

Experiments



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Experiments

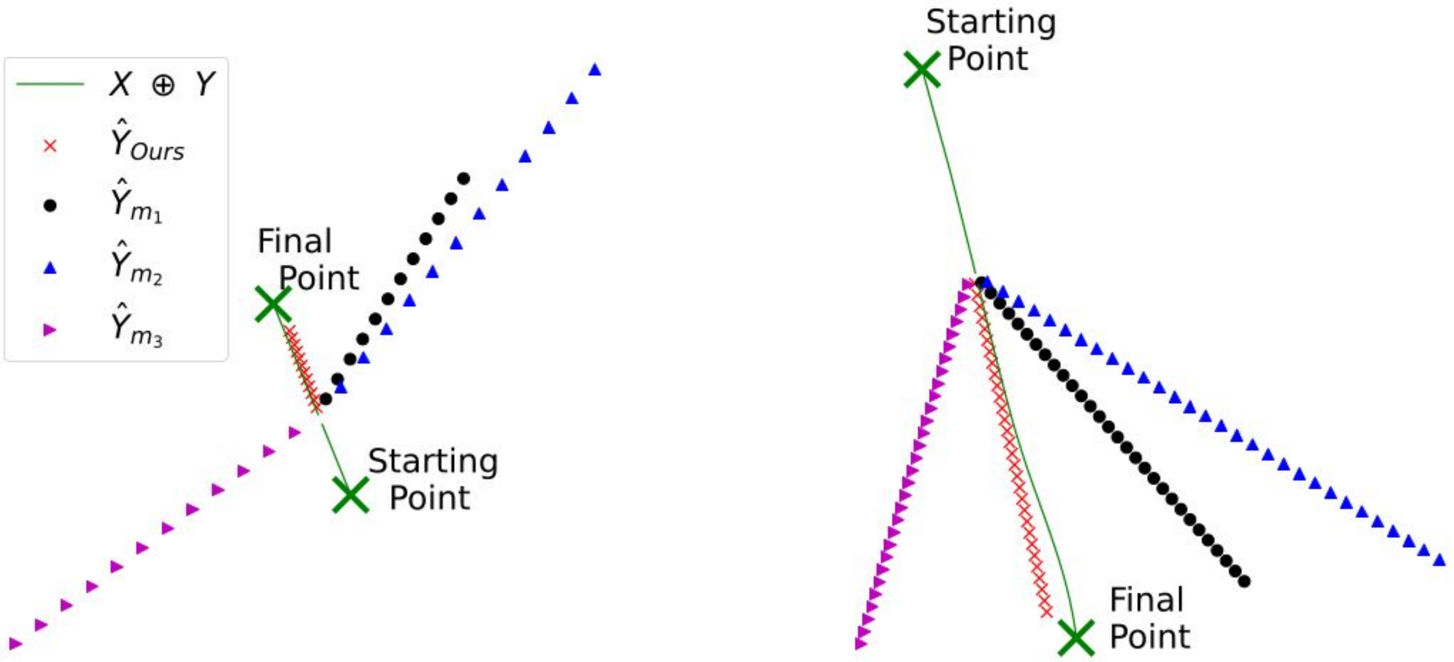
ADE/FDE METRICS (IN METERS) FOR 2 CLUSTERS OF THE TEST SET.

		Baselines		Ours		
Data set	Cluster ID (# samples)	LSTM [22]	CF VAN GAN [14]	CF VAN GAN + wL2	CF VAN GAN + wB	CF VAN GAN +wL2 + wB
THÖR	9 (23)	1.203 2.456	1.120 ± 0.025 2.758 ± 0.082	1.054 ± 0.048 2.505 ± 0.134	1.124 ± 0.038 2.811 ± 0.136	$\mathbf{1.039 \pm 0.055}$ $\mathbf{2.505 \pm 0.105}$
	0 (1003)	0.325 0.447	$\mathbf{0.311 \pm 0.003}$ $\mathbf{0.403 \pm 0.010}$	0.321 ± 0.004 0.419 ± 0.015	0.317 ± 0.007 0.416 ± 0.021	0.315 ± 0.002 0.424 ± 0.017
Argoverse	10 (16)	7.394 19.075	7.184 ± 0.178 18.402 ± 0.415	7.105 ± 0.123 18.233 ± 0.297	7.122 ± 0.055 18.276 ± 0.113	$\mathbf{7.047 \pm 0.088}$ $\mathbf{18.128 \pm 0.194}$
	18 (1542)	0.912 1.148	0.809 ± 0.016 1.100 ± 0.017	0.807 ± 0.010 1.088 ± 0.027	0.805 ± 0.007 1.079 ± 0.012	$\mathbf{0.795 \pm 0.008}$ $\mathbf{1.055 \pm 0.030}$

Experiments

ADE/FDE METRICS (IN METERS) IN THE TEST SETS FOR *ideal* MODELS. THESE CAN BE SEEN AS LOWER BOUNDS.

Data set	cGAN	Ours
THÖR	0.657 ± 0.003 1.114 ± 0.011	$\mathbf{0.591 \pm 0.014}$ $\mathbf{0.937 \pm 0.022}$
Argoverse	1.927 ± 0.016 3.323 ± 0.030	$\mathbf{1.785 \pm 0.014}$ $\mathbf{2.887 \pm 0.038}$

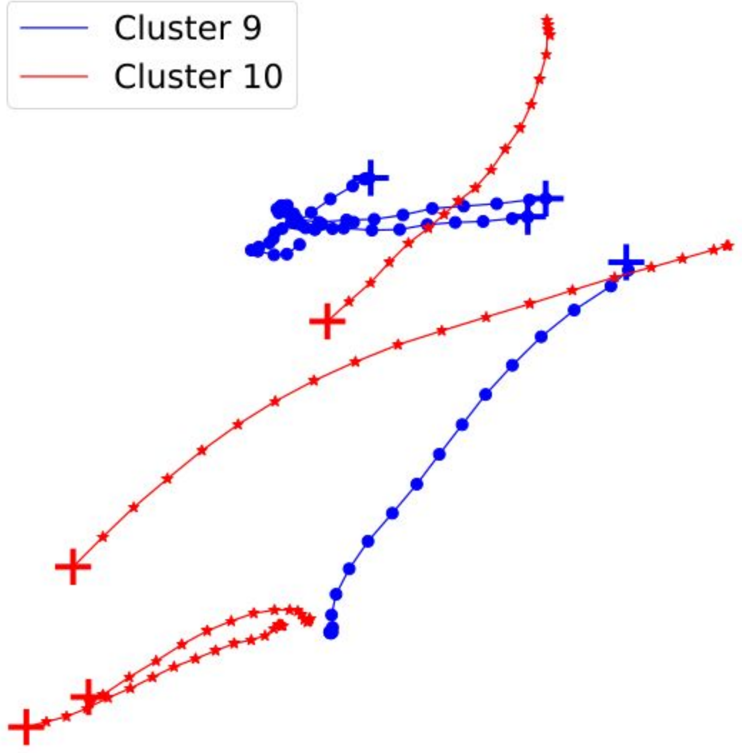


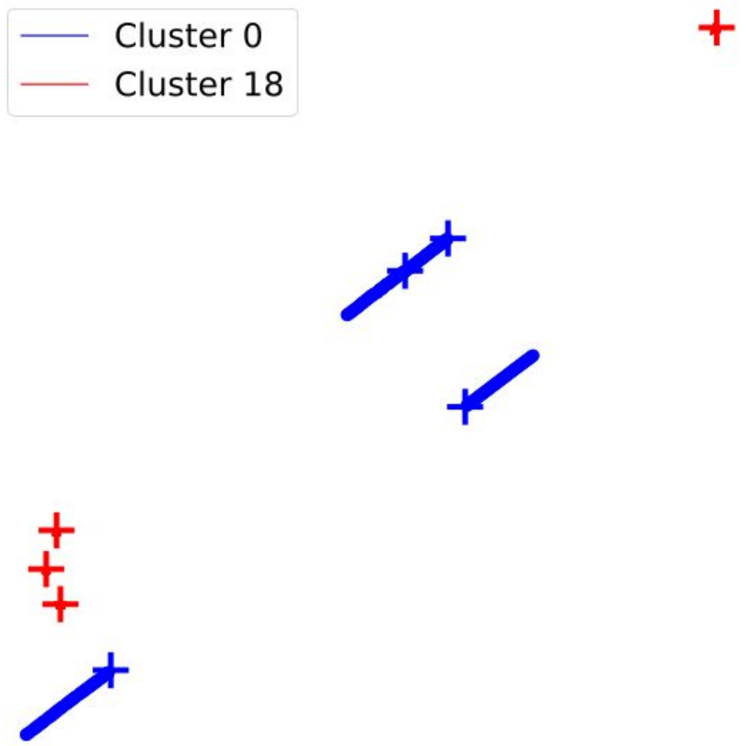
Conclusions

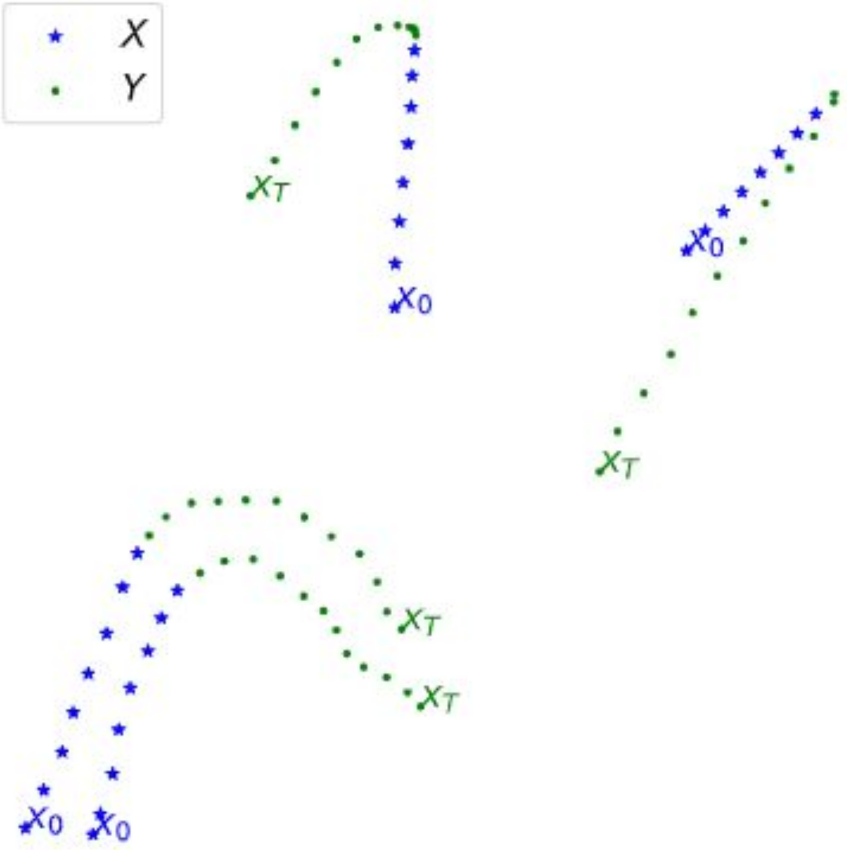
- We adapted Self-conditioned GAN to trajectory generation task
- We **improved ADE/FDE** of least representative supervised and unsupervised groups of trajectories
- We **improved globally** in human trajectory data (THÖR)
- We obtained **competitive global results** in road agents trajectory data (Argoverse)

Conclusions

- Modes from our system represent the first step to identify different behaviors from trajectories







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