ACM Multimedia 2022
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Diverse Human Motion Prediction via Gumbel-Softmax Sampling from an Auxiliary Space

    

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Human Motion Prediction (HMP)

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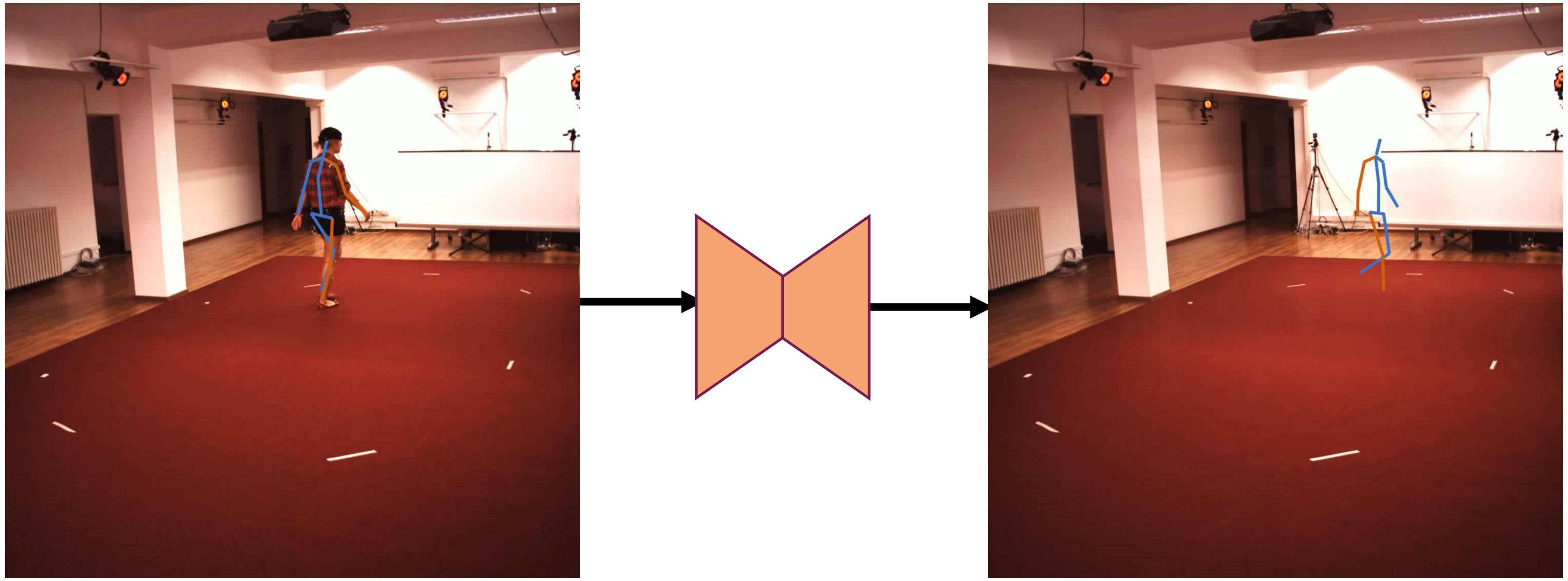

Observed Seq Future Seq

Applications

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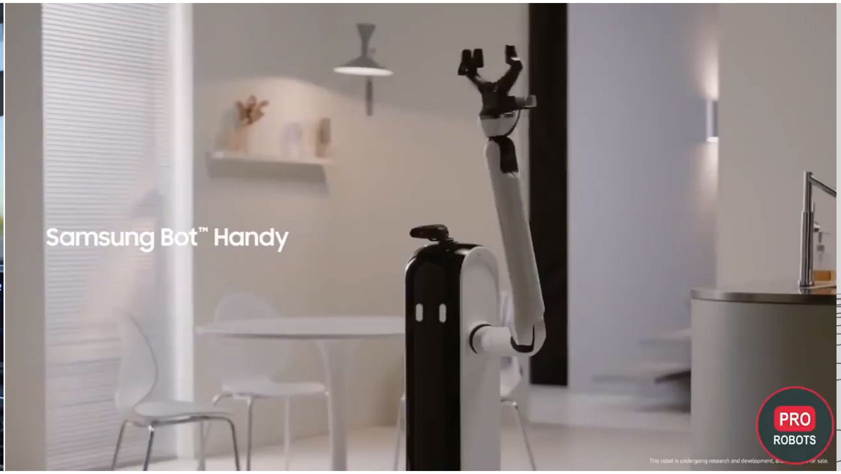
autonomous driving



human-computer interaction

animation creation

Deterministic HMP

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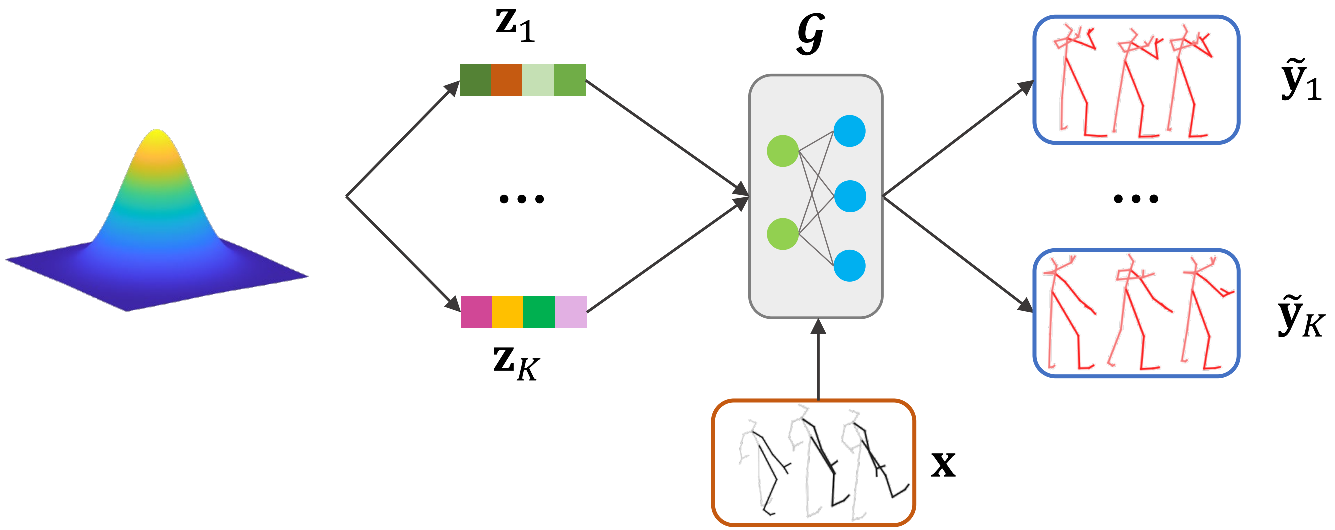
- Predict only one motion in the future
- Ignore the uncertainty of human motion
- Cannot satisfy some safety-critical applications

LTD Mao W, *et al.*, ICCV 2019
HisReps Mao W, *et al.*, ECCV 2020
LDR Cui Q, *et al.*, CVPR 2020
MSR Dang L, *et al.*, ICCV 2021
MLMA Mao W, *et al.*, IJCV 2021
PGBIG Ma T, *et al.*, CVPR 2022

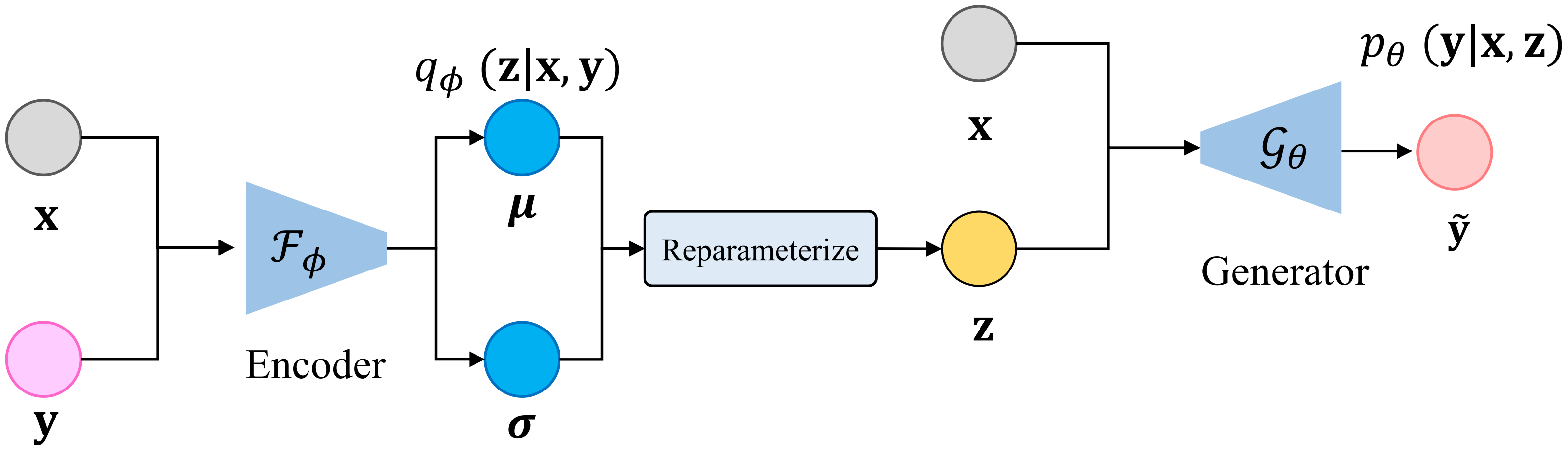
Stochastic and Diverse HMP

- Adopt deep generative networks, *e.g.* GAN or CVAE to model the conditional distribution of future poses given previous ones
- Sample random noises and decode them into multiple possible future motions



Hp-gan Barsoum E, *et al.*, CVPR 2018 **Bihmp-gan** Kundu J, *et al.*, AAAI 2019 **MNM** Li B, *et al.*, TIP 2020

Example: CVAE-based Approach



- Introduce an approximate posterior $q(\mathbf{z}|\mathbf{x},\mathbf{y})$ and maximizing the ELBO:

$$\log p(\mathbf{y} \mid \mathbf{x}) = \log \int p(\mathbf{y} \mid \mathbf{x}, \mathbf{z}) p(\mathbf{z}) d\mathbf{z} = \log \int \frac{p(\mathbf{y} \mid \mathbf{x}, \mathbf{z}) p(\mathbf{z})}{q(\mathbf{z} \mid \mathbf{x}, \mathbf{y})} q(\mathbf{z} \mid \mathbf{x}, \mathbf{y}) d\mathbf{z} \geq \mathbb{E}_q \log \frac{p(\mathbf{y} \mid \mathbf{x}, \mathbf{z}) p(\mathbf{z})}{q(\mathbf{z} \mid \mathbf{x}, \mathbf{y})}$$

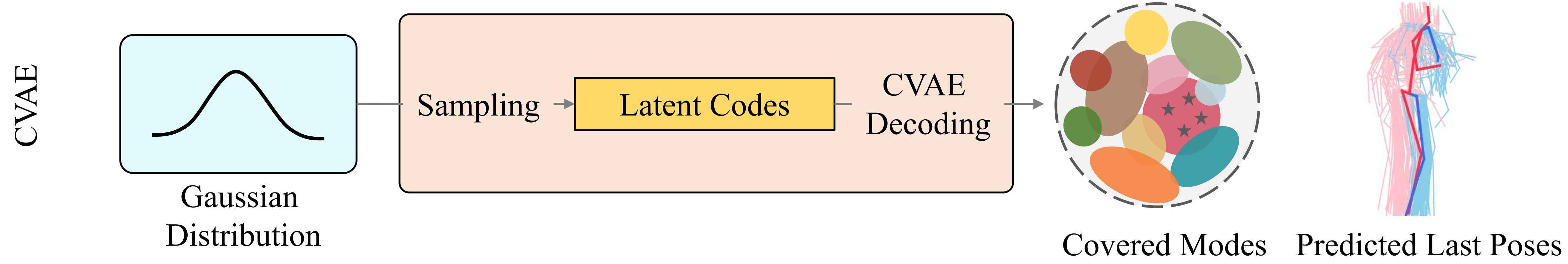
- Model the two distributions of $q\ (\mathbf{z}|\mathbf{x},\mathbf{y})$ and $p\ (\mathbf{y}|\mathbf{x},\mathbf{z})$ by two neural networks $\mathcal{F}_\phi$ and $\mathcal{G}_\theta$, and estimates their parameters by optimizing the following loss function

$$\mathcal{L}(\mathbf{y}, \boldsymbol{\phi}, \boldsymbol{\theta}) = -\mathcal{KL}(q_\phi(\mathrm{z} \mid \mathbf{x}, \mathbf{y}) \| p(\mathrm{z})) + \mathbb{E}_{q_\phi} \log p_{\boldsymbol{\theta}}(\mathbf{y} \mid \mathbf{x}, \mathbf{z})$$

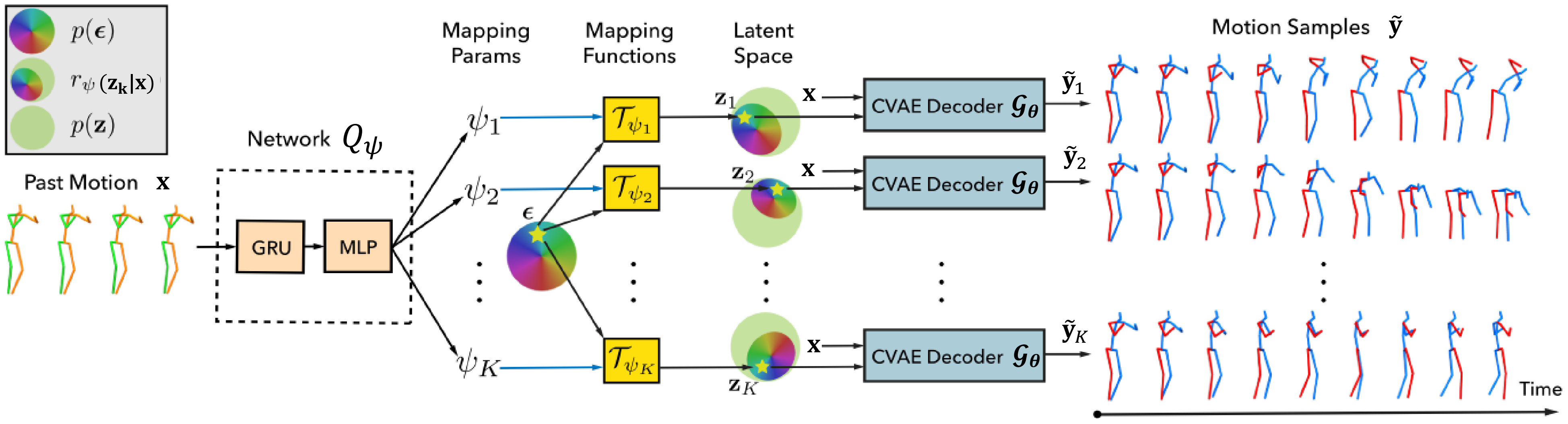
AEVB Kingma D, *et al.*, arXiv 2013

Limitations

- learns an imbalanced multimodal conditional distribution
- Latent codes correspond to the dominant modes, while ignoring other minor modes



Stochastic and Diverse HMP: DLow



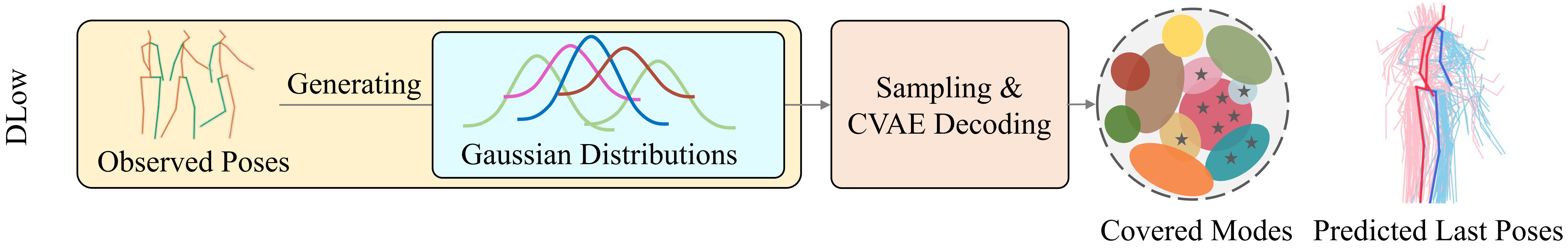
- Given x, they used a network Q_ψ to generate *K* Gaussian distributions $\{(\mathbf{A}_k, \mathbf{b}_k)\}_{k=1}^{K} = Q_\psi(\mathbf{x})$
- Then, they predicted *K* results by

$$\epsilon \sim \mathcal{N}(0,1)$$
$$\mathbf{z}_k = \mathbf{A}_k \epsilon + \mathbf{b}_k, \quad 1 \le k \le K$$
$$\mathbf{y}_k = \mathcal{G}_\theta(\mathbf{x}, \mathbf{z}_k), \quad 1 \le k \le K.$$

DLow Ye Y, *et al.*, ECCV 2020

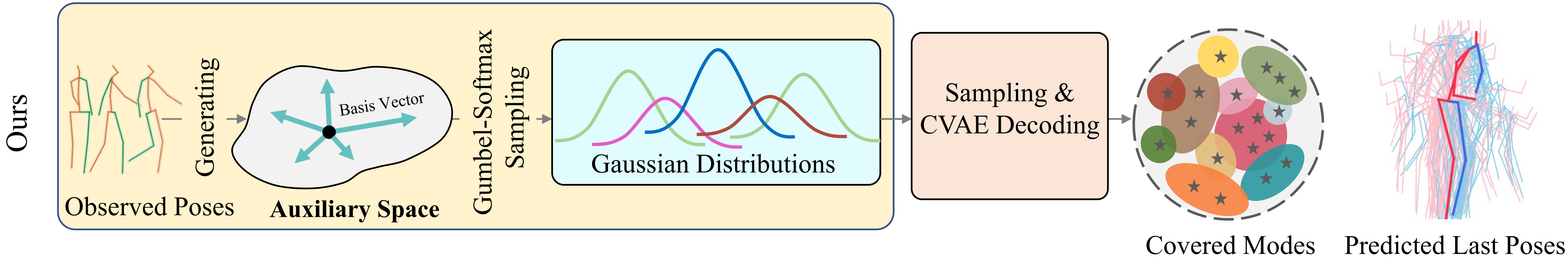
Limitations

- Can only generate a fixed number of Gaussian distributions
- Entangles the performance of diverse prediction with the learning of the network parameters, requiring to consider all training data and make tradeoffs

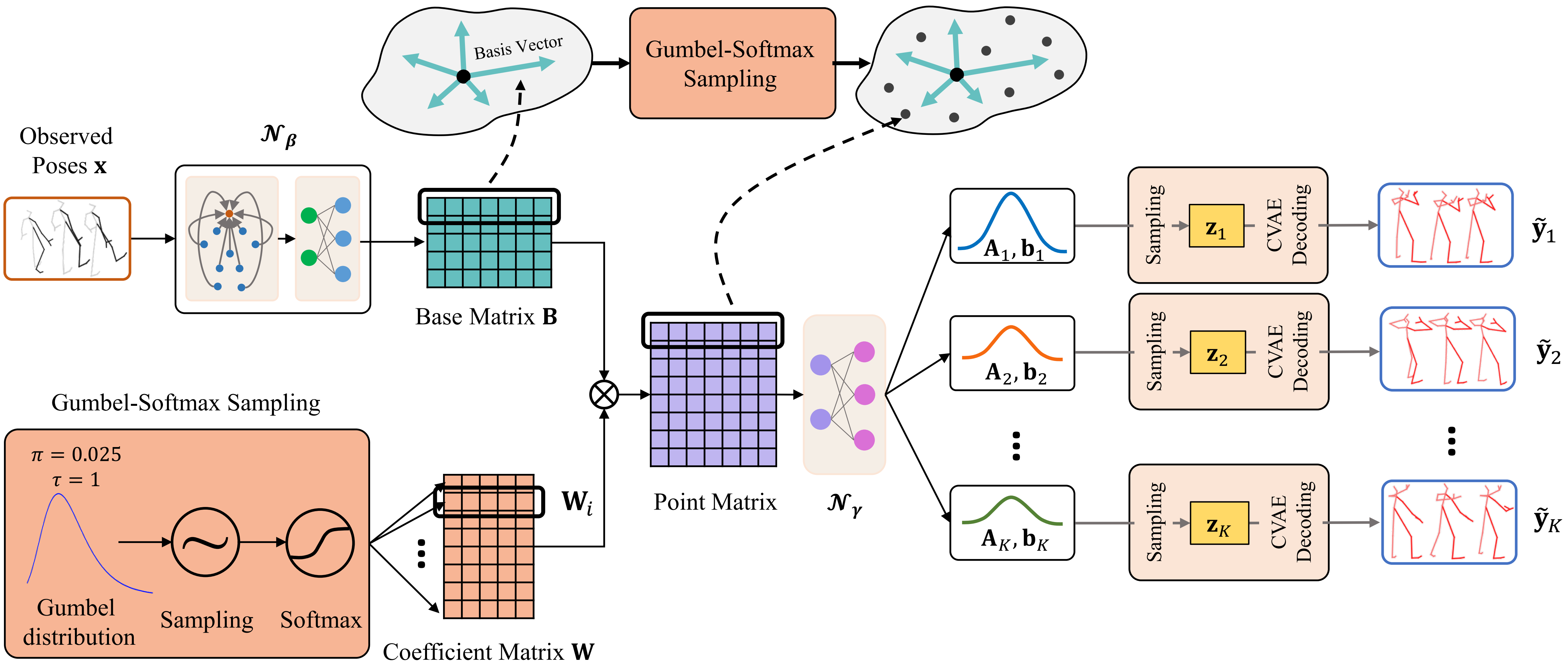


Our Method: Key Insights

- Learn an auxiliary space then sample points from the it and map them to Gaussian distributions which finally correspond to different modes of the target distribution
- Disentangles the correlation between diverse prediction and the network parameter learning
- Arbitrary number of samples can be generated after the auxiliary space is built



Our Method



Basis Vector
Gumbel-Softmax Sampling
Observed Poses x
$\mathcal{N}_\beta$
Base Matrix **B**
Gumbel-Softmax Sampling
$\pi = 0.025$
$\tau = 1$
Gumbel distribution
Sampling
Softmax
$\mathbf{W}_i$
Coefficient Matrix **W**
Point Matrix
$\mathcal{N}_\gamma$
$\mathbf{A}_1, \mathbf{b}_1$
$\mathbf{A}_2, \mathbf{b}_2$
$\mathbf{A}_K, \mathbf{b}_K$
Sampling
$\mathbf{z}_1$
$\mathbf{z}_2$
$\mathbf{z}_K$
CVAE Decoding
$\tilde{\mathbf{y}}_1$
$\tilde{\mathbf{y}}_2$
$\tilde{\mathbf{y}}_K$

Training Losses

- Hinge-diversity loss

$$\mathcal{L}_{hdiv} = \frac{1}{K(K-1)} \sum_{i=1}^{K} \sum_{j \neq i}^{K} \mathbf{max}\left(0, \eta - \left\|\tilde{\mathbf{y}}_i - \tilde{\mathbf{y}}_j\right\|_2\right)$$

- Accuracy loss

$$\mathcal{L}_{acc} = \min_{k} \|\mathbf{y} - \tilde{\mathbf{y}}_k\|_2, k \in [1, K]$$

- KL loss

$$\mathcal{L}'_{KL} = \mathcal{KL}(r_{\beta,\gamma}(\mathbf{z}_k \mid \mathbf{x}) \| p(\mathbf{z})), k \in [1, K]$$

Quantitative Results

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All the results are calculated by sampling 50 times for each input historical pose sequence.

	Method	Human3.6M [22]					HumanEva-I [44]				
		APD ↑	ADE ↓	FDE ↓	MMADE ↓	MMFDE ↓	APD ↑	ADE ↓	FDE ↓	MMADE ↓	MMFDE ↓
deterministic	LTD [37]	0.000	0.516	0.756	0.627	0.795	0.000	0.415	0.555	0.509	0.613
	MSR [15]	0.000	0.508	0.742	0.621	0.791	0.000	0.371	0.493	0.472	0.548
stochastic	Pose-Knows [49]	6.723	0.461	0.560	0.522	0.569	2.308	0.269	0.296	0.384	0.375
	MT-VAE [50]	0.403	0.457	0.595	0.716	0.883	0.021	0.345	0.403	0.518	0.577
	HP-GAN [6]	7.214	0.858	0.867	0.847	0.858	1.139	0.772	0.749	0.776	0.769
	BoM [7]	6.265	0.448	0.533	0.514	0.544	2.846	0.271	0.279	0.373	0.351
	GMVAE [16]	6.769	0.461	0.555	0.524	0.566	2.443	0.305	0.345	0.408	0.410
	DeLiGAN [21]	6.509	0.483	0.534	0.520	0.545	2.177	0.306	0.322	0.385	0.371
	DSF [51]	9.330	0.493	0.592	0.550	0.599	4.538	0.273	0.290	0.364	0.340
	DLow [52]	11.741	0.425	0.518	0.495	0.531	4.855	0.251	0.268	0.362	0.339
	GSPS [36]	14.757	0.389	0.496	0.476	0.525	5.825	0.233	0.244	0.343	0.331
	Ours	**15.310**	**0.370**	**0.485**	**0.475**	**0.516**	**6.109**	**0.220**	**0.234**	**0.342**	**0.316**

MSR Dang L, *et al.*, ICCV 2021 **GSPS Mao W**, *et al.*, ICCV 2021 (Oral) **DLow** Ye Y, *et al.*, ECCV 2020

Qualitative Results

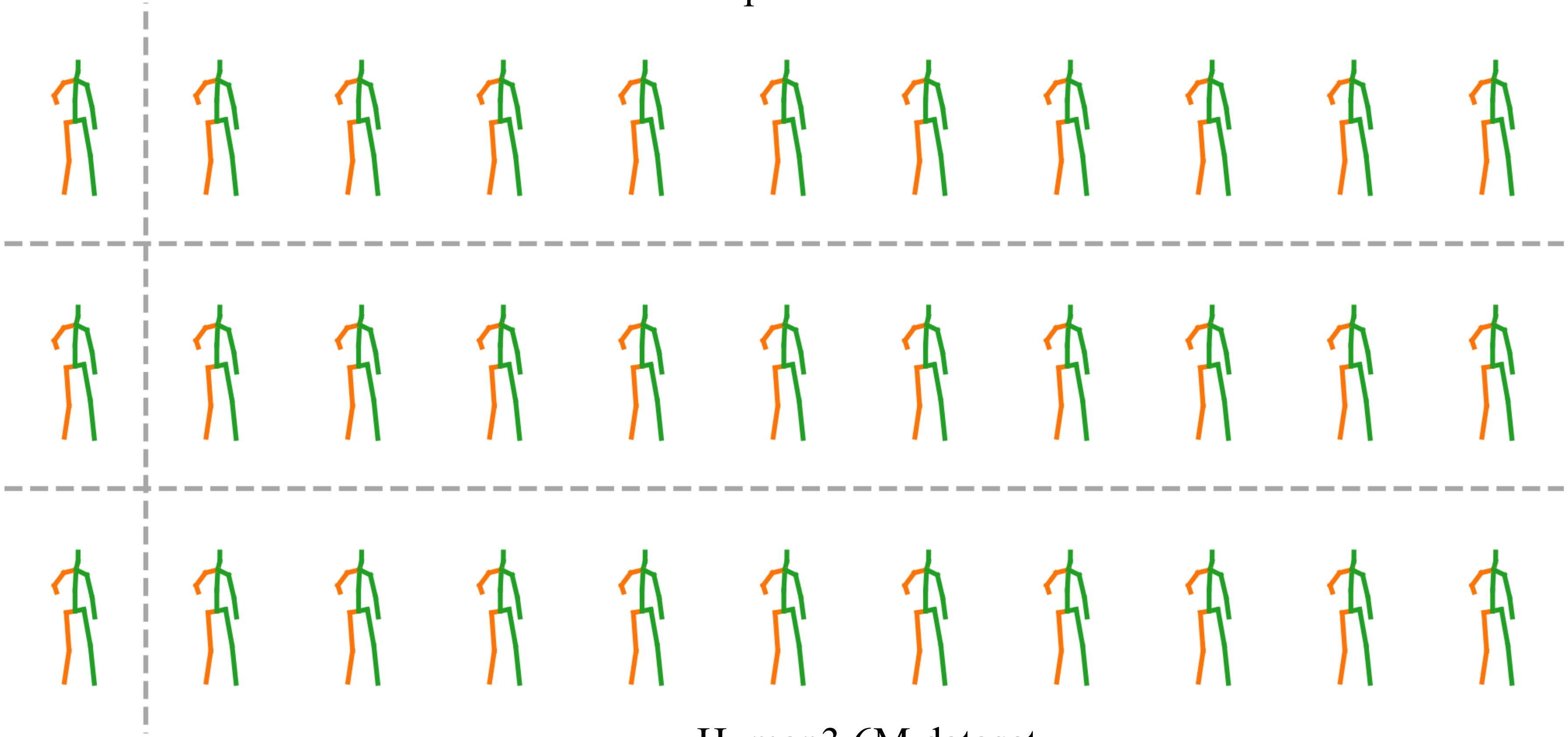
GT

10 predicted results

DLow
(12.367)

GSPS
(15.177)

Ours
(16.463)

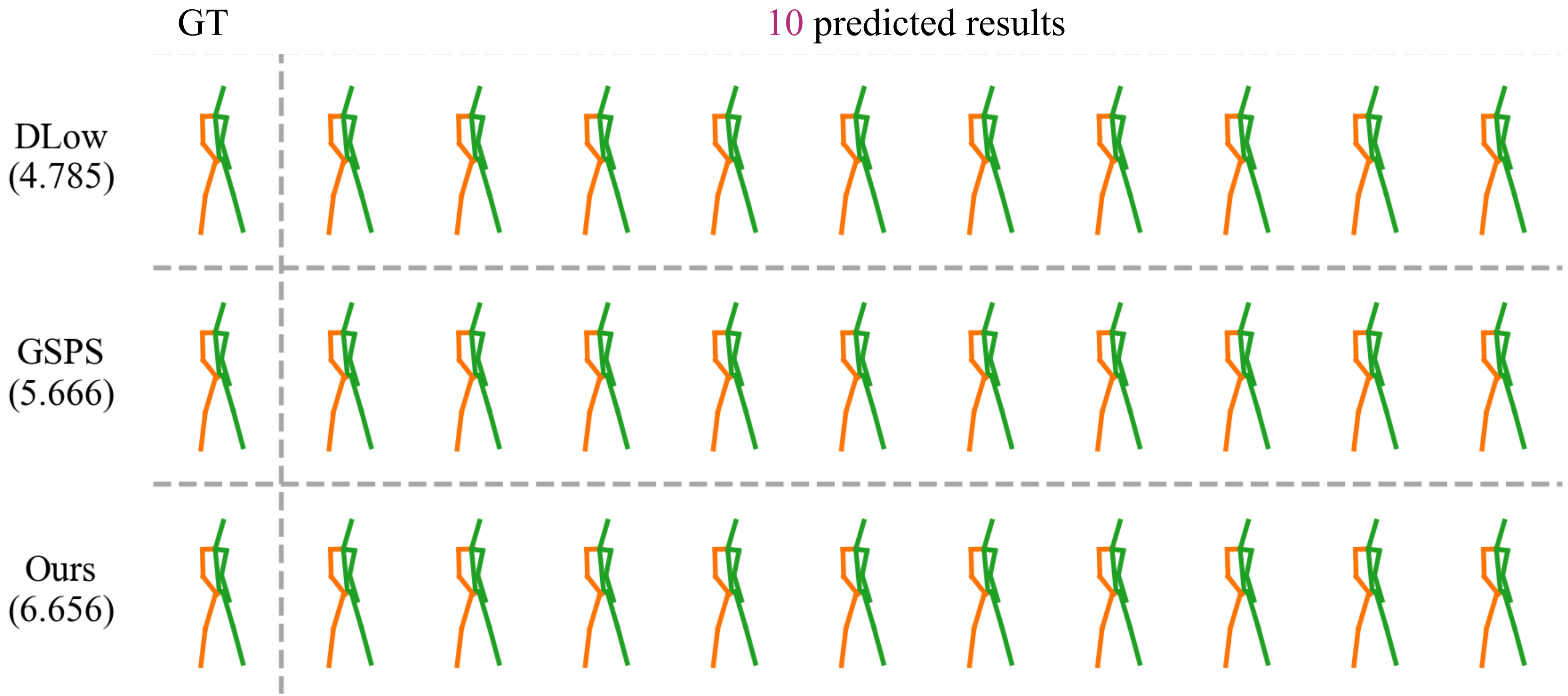


Human3.6M dataset

DLow Ye Y, *et al.*, ECCV 2020

GSPS Mao W, *et al.*, ICCV 2021 (Oral)

Qualitative Results



HumanEva-I dataset

DLow Ye Y, *et al.*, ECCV 2020

GSPS Mao W, *et al.*, ICCV 2021 (Oral)

Qualitative Results

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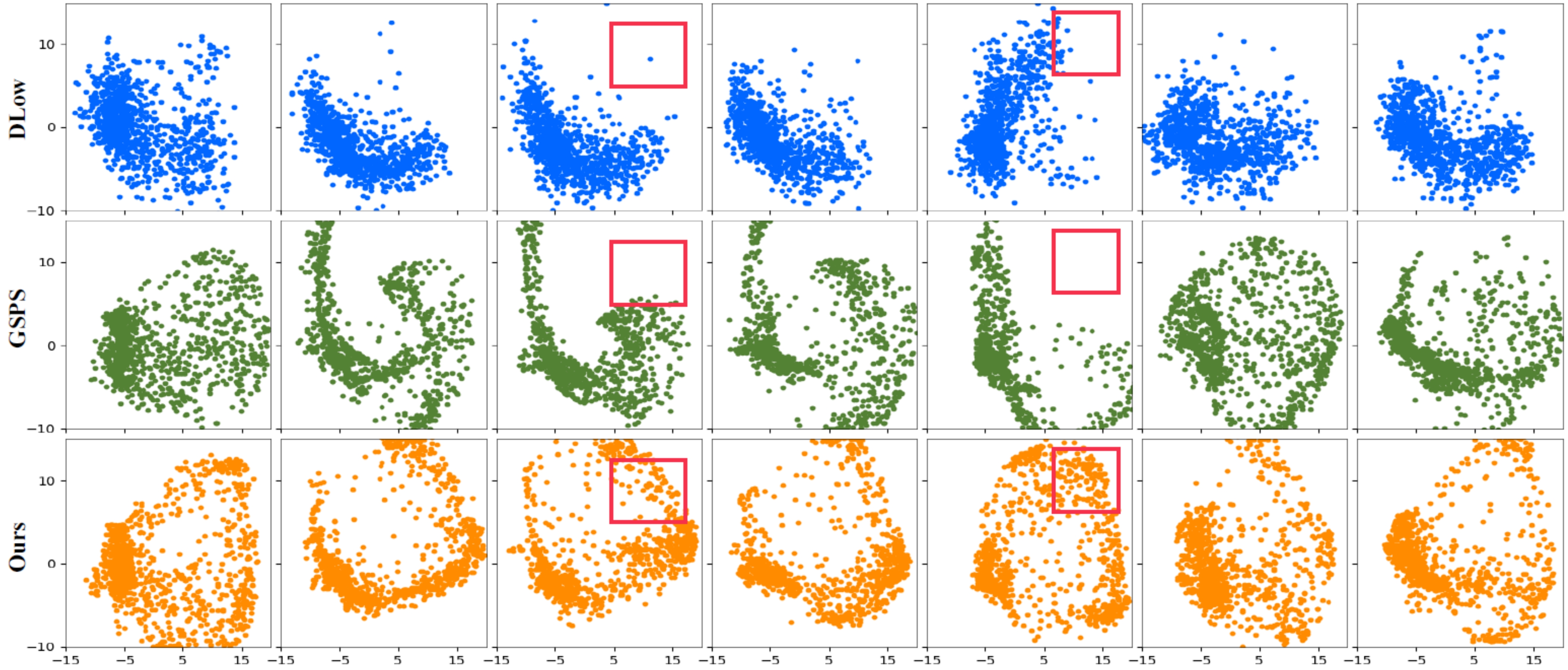

DLow Ye Y, *et al.*, ECCV 2020 **GSPS** Mao W, *et al.*, ICCV 2021 (Oral)

QR Code for our project:

https://github.com/Droliven/diverse_sampling

Thank you!

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