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

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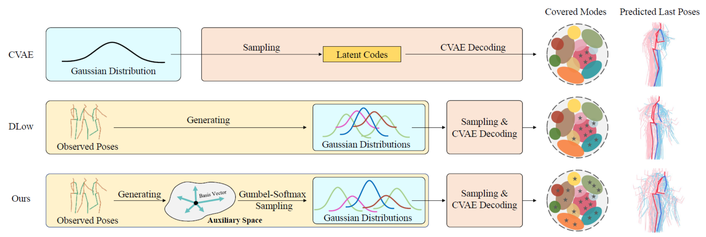
Background & Motivation

- Diverse human motion prediction aims at predicting multiple possible future sequences from the observed one.
- Poses obtained by previous simple deep generative networks are not diverse enough.
- Recent work attempted to model the conditional distribution of data but it can only cover a fixed number of modes.
- We propose a novel sampling strategy for sampling very diverse results from an imbalanced multimodal distribution.



Contributions

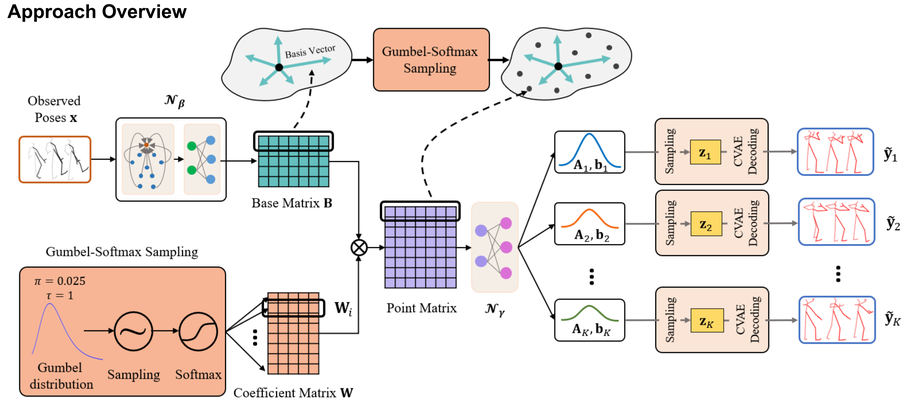
- A novel sampling method converts the sampling of the distribution into randomly sampling of points from an auxiliary space for diverse and accurate sampling.
- A Gumbel-Softmax sampling method and a hinge-diversity loss both improve the performance of our method.
- Extensive experimental results demonstrate the effectiveness of our approach.

Datasets & Metric & Project

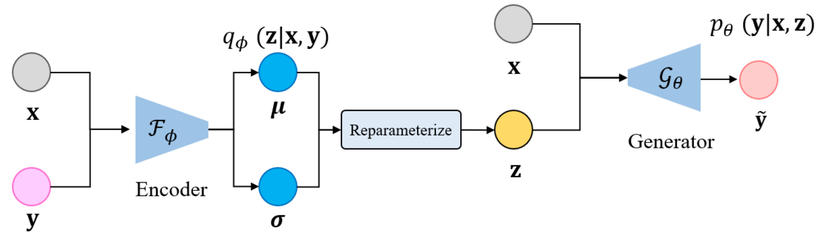
- Datasets: Human3.6M, HumanEva-I Dataset
- Metrics: APD, ADE, FDE, MMADE, MMFDE
- Link: https://github.com/Droliven/diverse_sampling

Proposed Approach

Approach Overview



Architecture of the pretrained CVAE



Pseudocode for the overall approach and the Gumbel-Softmax sampling strategy

Algorithm 1 Diverse sampling from a complex distribution by random Gumbel-Softmax sampling from an auxiliary space

Input: Observed pose sequence $\mathbf{x}$, number of samples K, auxiliary space generation network $\mathcal{N}_\beta$, Gaussian distribution generation network $\mathcal{N}_\gamma$, CVAE decoder network $\mathcal{G}_\theta$ that models the target complex distribution
Output: A set of samples $\{\tilde{\mathbf{y}}_k\}_{k=1}^K$

$\mathbf{B} = \mathcal{N}_\beta(\mathbf{x})$ // *generate an auxiliary space given input poses*
$\mathbf{W} \leftarrow$ Gumbel-Softmax sampling // *generate a coefficient matrix by* Algorithm 2
$\mathbf{P} = \mathbf{WB}$ // *Multiply* $\mathbf{W}$ *and* $\mathbf{B}$ *to obtain a point matrix* $\mathbf{P}$
$\{\mathbf{A}_k, \mathbf{b}_k\}_{k=1}^K = \mathcal{N}_\gamma(\mathbf{P})$ // *convert points into means and variances*
$\epsilon \sim \mathcal{N}(0,1)$ // *sampling an* ϵ *from the normal distribution*
for $k = 1$ to K **do**
  $\mathbf{z}_k = \mathbf{A}_k \epsilon + \mathbf{b}_k$ // *sample* $\mathbf{z}_k$ *from Gaussian distribution of variance* $\mathbf{A}_k$ *and mean* $\mathbf{b}_k$ *by reparameterization trick*
  $\tilde{\mathbf{y}}_k = \mathcal{G}_\theta(\mathbf{x}, \mathbf{z}_k)$ // *decode* $\mathbf{z}_k$ *and* $\mathbf{x}$ *into a result* $\tilde{\mathbf{y}}_k$
end for

Algorithm 2 Gumbel-Softmax coefficient matrix generation

Input: Number of coefficient vectors K, dimension size M of a coefficient vector, Gumbel distribution parameters π and τ
Output: A coefficient matrix $\mathbf{W} \in \mathbb{R}^{K \times M}$

Declare a matrix $\mathbf{W} \in \mathbb{R}^{K \times M}$
for $i = 1$ to K **do**
  for $j = 1$ to M **do**
    $u \sim \mathrm{U}(0,1)$ // *sample a value from uniform distribution*
    $g = -\log(-\log(u))$
    $\mathbf{W}_{ij} = \frac{\pi + g}{\tau}$
  end for
  $\mathbf{W}_i = \mathrm{Softmax}(\mathbf{W}_i)$ // *normalize the* i^{th} *row of* $\mathbf{W}$
end for

Loss functions

$$\mathcal{L}_{hdiv} = \frac{1}{K(K-1)} \sum_{i=1}^{K} \sum_{j \neq i}^{K} \max\left(0, \eta - \|\tilde{\mathbf{y}}_i - \tilde{\mathbf{y}}_j\|_2\right) \quad \mathcal{L}_{acc} = \min_k \|\mathbf{y} - \tilde{\mathbf{y}}_k\|_2, k \in [1, K] \quad \mathcal{L}'_{KL} = \mathcal{KL}(r_{\beta,\gamma}(\mathbf{z}_k \mid \mathbf{x}) \| p(\mathbf{z})), k \in [1, K]$$

Quantitative Results

Comparisons with baselines

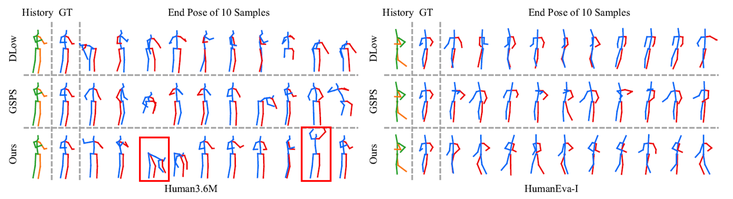
	Method	Human3.6M [18]					HumanEva-I [36]				
		APD ↑	ADE ↓	FDE ↓	MMADE ↓	MMFDE ↓	APD ↑	ADE ↓	FDE ↓	MMADE ↓	MMFDE ↓
deterministic	LTD [31]	0.000	0.516	0.756	0.627	0.795	0.000	0.415	0.555	0.509	0.613
	MSR [13]	0.000	0.508	0.742	0.621	0.791	0.000	0.371	0.493	0.472	0.548
stochastic	Pose-Knows [41]	6.723	0.461	0.560	0.522	0.569	2.308	0.269	0.296	0.384	0.375
	MT-VAE [42]	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 [14]	6.769	0.461	0.555	0.524	0.566	2.443	0.305	0.345	0.408	0.410
	DeLiGAN [17]	6.509	0.483	0.534	0.520	0.545	2.177	0.306	0.322	0.385	0.371
	DSF [43]	9.330	0.493	0.592	0.550	0.599	4.538	0.273	0.290	0.364	0.340
	DLow [44]	11.741	0.425	0.518	0.495	0.531	4.855	0.251	0.268	0.362	0.339
	GSPS [30]	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**

Ablation study results

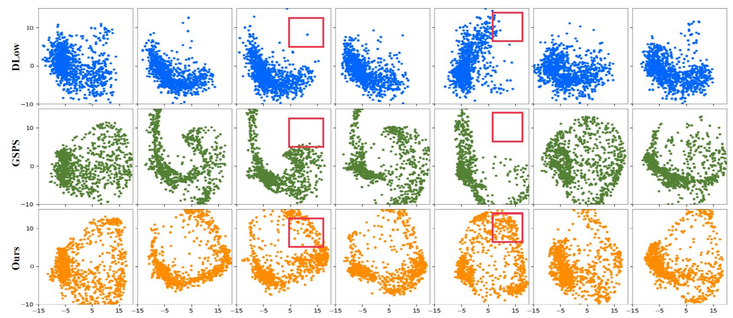
	① Number of basis vectors					② Dimension of auxiliary space					③ Sampling method		④ $N_\mathcal{T}$		⑤ $\mathcal{L}_{hdiv}$ vs. $\mathcal{L}_{div}$		
	20	30	40*	50	60	32	64	128*	256	512	Gumbel*	Gaussian	Uniform	w/ $N_\mathcal{T}$*	w/o $N_\mathcal{T}$	$\mathcal{L}_{hdiv}$(25)*	$\mathcal{L}_{div}$ (25)	$\mathcal{L}_{div}$ (1300)
APD ↑	5.929	5.946	**5.993**	5.969	5.951	5.885	5.931	**5.993**	5.963	5.957	**5.993**	5.847	5.730	**5.993**	5.182	**5.993**	3.843	**5.993**
ADE ↓	0.234	0.234	0.231	**0.229**	0.233	0.236	0.233	**0.231**	0.233	0.236	**0.231**	0.240	0.233	0.231	**0.229**	0.231	**0.211**	0.235
FDE ↓	0.240	0.243	0.240	**0.239**	0.241	0.245	0.243	**0.240**	0.241	0.243	**0.240**	0.246	0.241	0.240	**0.236**	0.240	**0.218**	0.242
MMADE ↓	0.345	0.345	0.340	0.339	**0.338**	0.337	0.342	0.340	**0.336**	0.342	**0.340**	0.343	0.344	0.340	**0.322**	0.340	**0.309**	0.343
MMFDE ↓	0.321	0.319	0.313	0.315	**0.312**	0.312	0.318	0.313	**0.310**	0.316	**0.313**	0.320	0.323	0.313	**0.298**	0.313	**0.287**	0.321

Qualitative Results

Comparisons with baselines



Holistic views of results after the dimension reduction by PCA



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Acknowledgement

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