DLME: Deep Local-flatness Manifold Embedding

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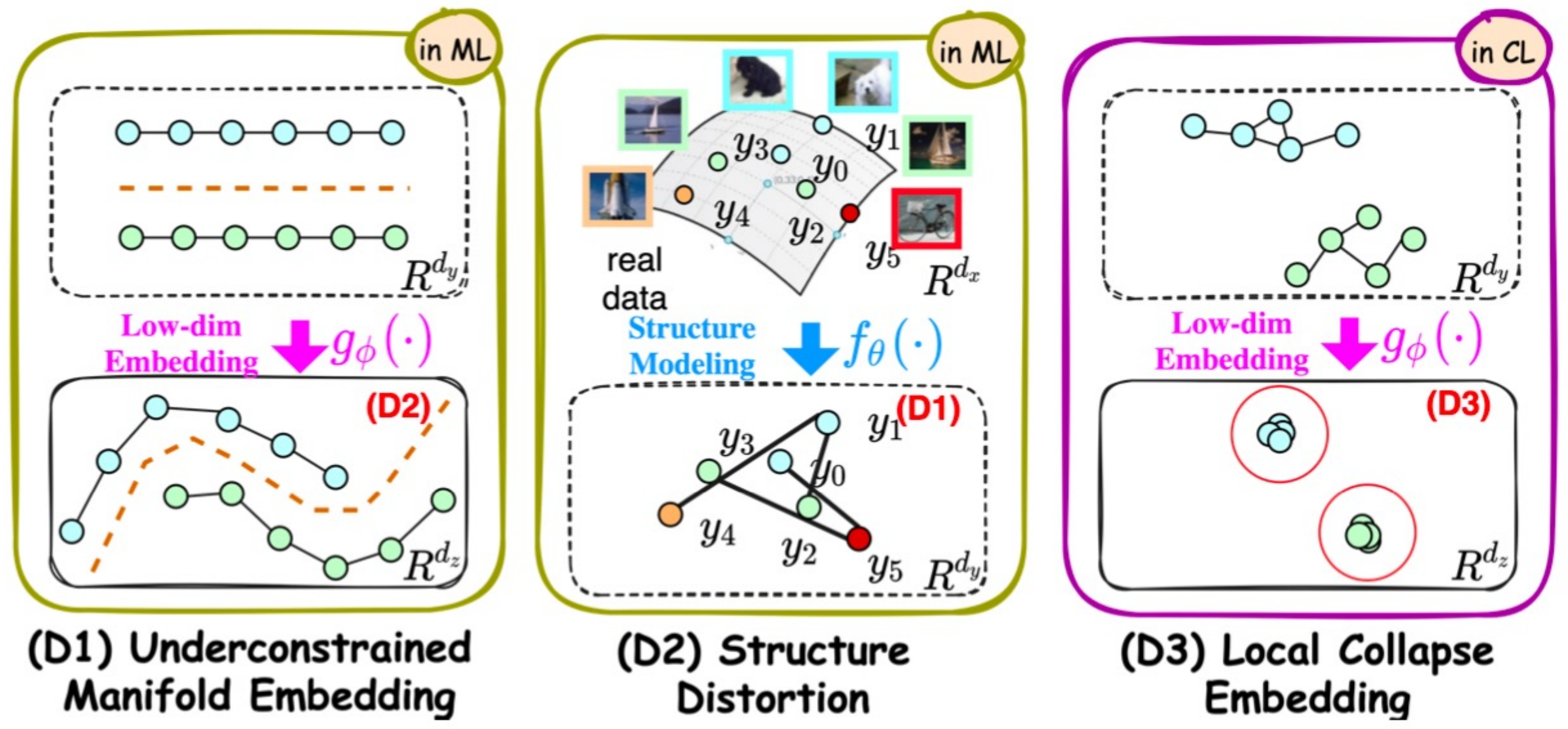
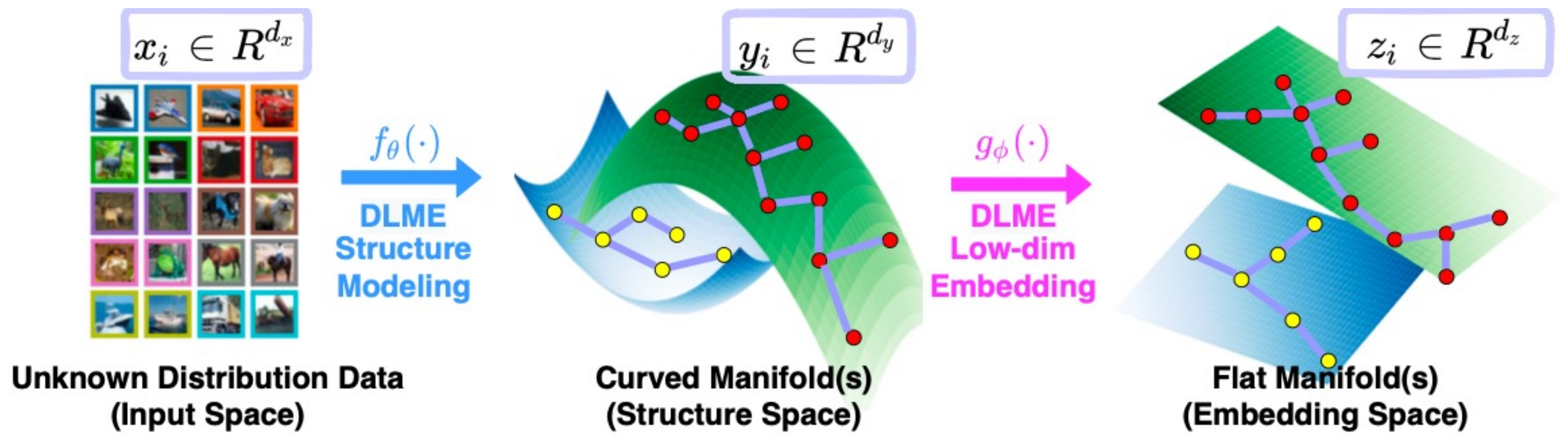
Background



(D1) Underconstrained Manifold Embedding (D2) Structure Distortion (D3) Local Collapse Embedding

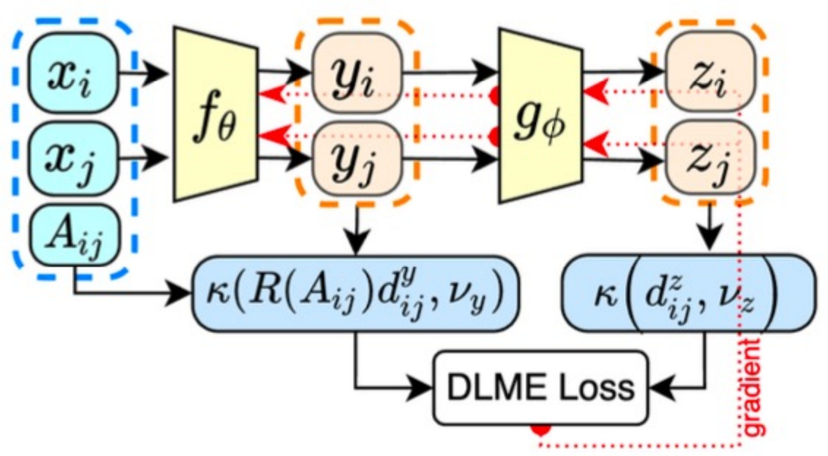
The application of the manifold learning method is limited, and we attribute the reasons to the following two reasons. (D1) **Under-constrained manifold embedding**. ML methods focus on local relationships, while it is prone to distorted embeddings that affect the performance of downstream tasks. (D2) **Structural distortion.** ML methods focus on handcraft or easy datasets and are not satisfactory in handling real-world datasets. (D3) Local collapse embedding. The unsmoothed loss of the CL leads to the model that is prone to local collapse and requires a large diversity of data to learn valid knowledge

Introduction



We propose a novel deep ML framework named deep local-flatness manifold embedding (DLME) to solve both problems by merging the advantages of ML and CL. Firstly, a **novel local flatness assumption** (LFA) is proposed to obtain a reasonable latent space by adding a second-order manifold curvature constraint (for D1). Secondly, a **new neural network framework** is designed to accommodate data augmentation and enhance the net work trainging (for D2). Furthermore, **an LFA-based smoother loss function** is designed to accommodate data augmentation. (for D3).

Method



The forward propagation of DLME:

$$y_i = f_\theta(x_i), y_i \in \mathbb{R}^{d_y}, x_i \sim \tau(x), x_j \sim \tau(x),$$

$$z_i = g_\phi(y_i), z_i \in \mathbb{R}^{d_z}, d_z < d_y,$$

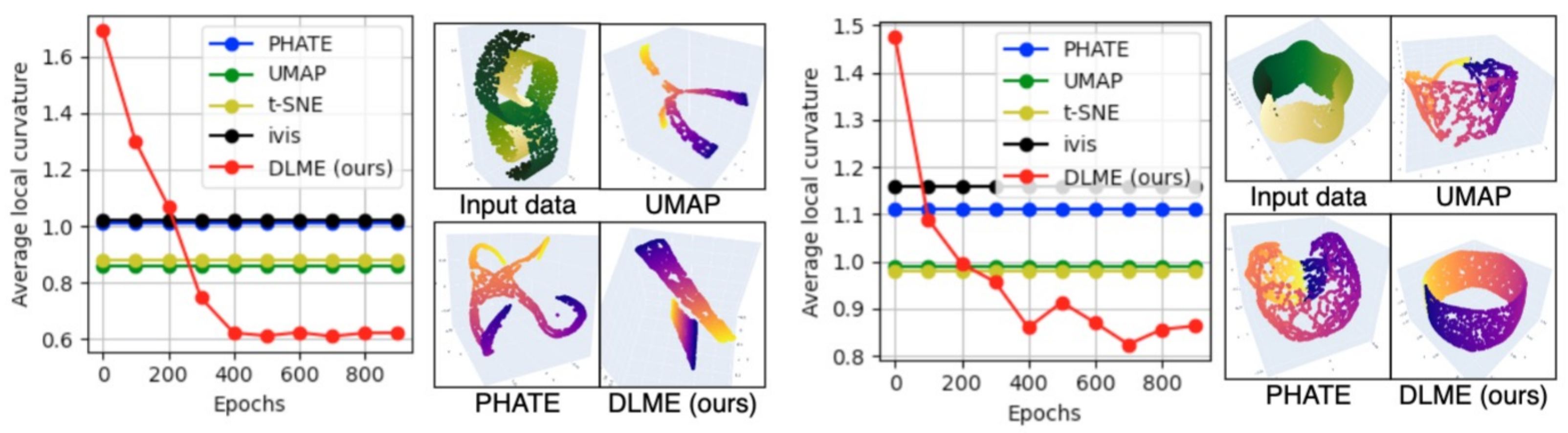
The loss function:

$$L_{\mathrm{D}} = E_{x_i,x_j}\left[\mathcal{D}\left(\kappa\left(R(A_{ij})d^y_{ij},\nu_y\right),\kappa\left(d^z_{ij},\nu_z\right)\right)\right]$$

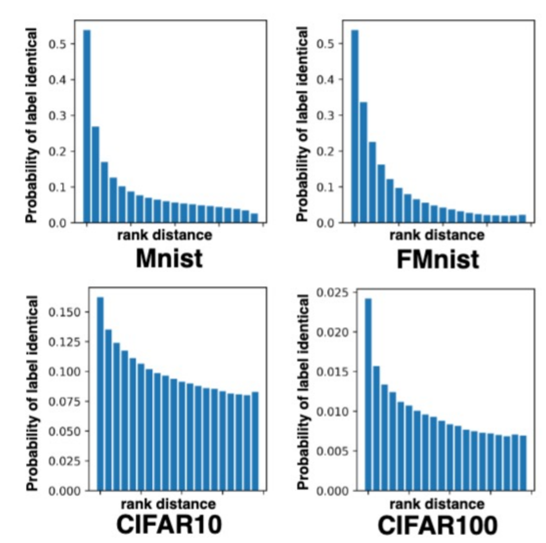
$$\mathcal{D}\left(p,q\right) = p\log q + (1-p)\log(1-q),$$

Where $\kappa(\,)$ is a similarity function, A_{ij} indicate weather input sample x_i and x_j are from same source image, z_i is a representation.

Experiments



(a) TwainSwissRoll Dataset (b) StarFruit Dataset



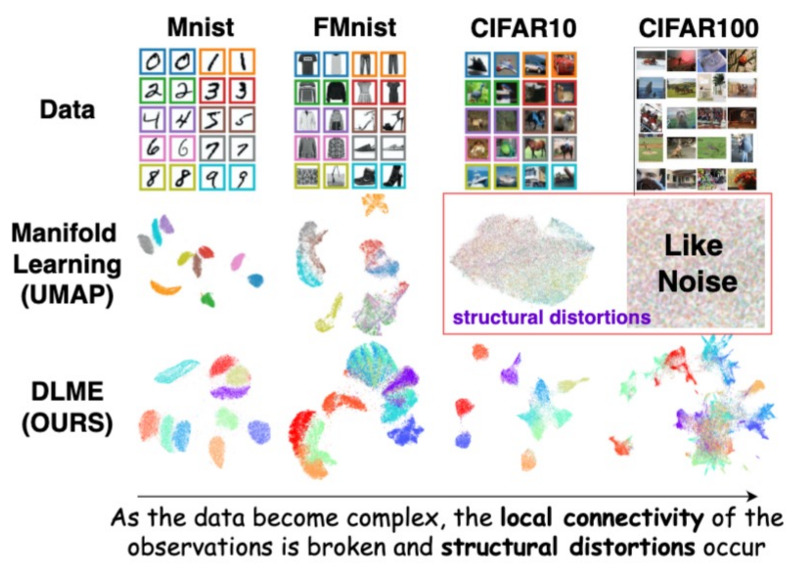


Table 1. Performance comparison on 12 datasets. **Bold** denotes the best result and **Underline** denotes 5% higher than others.

	Classification Accuracy (linear SVM)						Clustering Accuracy (K-means)					
	tSNE	UMAP	PUM	ivis	PHA	DLME	tSNE	UMAP	PUM	ivis	PHA	DLME
Digits	0.949	0.960	0.837	0.767	0.928	**0.973**	0.938	0.875	0.763	0.726	0.794	**0.956**
Coil20	0.799	0.834	0.774	0.672	0.828	**0.909**	0.763	0.821	0.722	0.612	0.655	**0.899**
Coil100	0.760	0.756	N/A	0.542	0.653	**0.952**	0.763	0.785	N/A	0.492	0.515	**0.944**
Mnist	0.963	0.966	0.941	0.671	0.796	**0.976**	0.904	0.801	0.772	0.466	0.614	**0.977**
EMnist	0.420	0.588	0.384	0.190	0.416	**0.657**	0.478	0.537	0.363	0.178	0.352	**0.641**
KMnist	0.738	0.656	0.674	0.547	0.607	**0.782**	0.586	0.668	0.706	0.522	0.594	**0.712**
Colon	0.932	0.893	0.918	0.942	0.930	**0.947**	0.862	0.847	0.861	0.922	0.855	**0.924**
Acti	0.861	0.844	0.849	0.831	0.798	**0.921**	0.784	0.639	0.783	0.681	0.679	**0.898**
MCA	0.719	0.675	0.667	0.634	0.552	**0.774**	0.475	0.532	0.464	0.443	0.414	**0.563**
Gast	0.821	0.846	0.706	0.687	0.676	**0.918**	0.534	0.546	0.512	0.427	0.523	**0.598**
SAMU	0.556	0.678	0.599	0.625	0.675	**0.700**	0.335	0.387	0.345	0.328	0.511	**0.572**
HCL	**0.884**	0.863	0.767	0.454	0.393	**0.884**	0.689	0.743	0.619	0.308	0.263	**0.753**

Observation: DLME brings notable and consistent improvements over base CL and ML methods.

Conclusions

We propose Deep Local-flatness Manifold Embedding (DLME), a novel ML framework to obtain reliable manifold embedding by reducing distortion. In the experiments, by demonstrating the effectiveness of DLME on downstream classification, clustering, and visualization tasks with three types of datasets (toy, biological, and image), our experimental results show that DLME outperforms SOTA ML & CL methods.

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