Self-Supervised Dimensionality Reduction with Neural Networks and Pseudo-labeling

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Introduction

- Processing high dimensional data is computationally very challenging
- need to develop dimensionality reduction(DR) methods
- **Challenge:** information loss should be minimum

Requirements of DR methods

- Quality
- Scalability
- Ease of Use
- Genericity
- Stability and Out-of-Sample Support
- Inverse Mapping
- Clustering

Background

PRINCIPAL COMPONENT ANALYSIS

Pros:

- Ease of Use
- Fast
- Highly scalable
- Out of sample capability

Cons:

- Lacks on quality
- Unable to capture non-linearity
- Not good for data visualization related to cluster analysis

Background

t-SNE

Pros:

- Ability to visually segregate similar samples
- Good for cluster analysis

Cons:

- High complexity $O(n^2)$
- Very sensitive to small data changes
- Hard to tune
- No out-of-sample capability

Background

Uniform Manifold Approximation and Projection (UMAP)

Pros:

- Generate visualizations comparable to t-SNE
- Much faster
- Out-of-sample capability

Cons:

- Very sensitive to small data changes
- Hard to tune

Background

Autoencoders

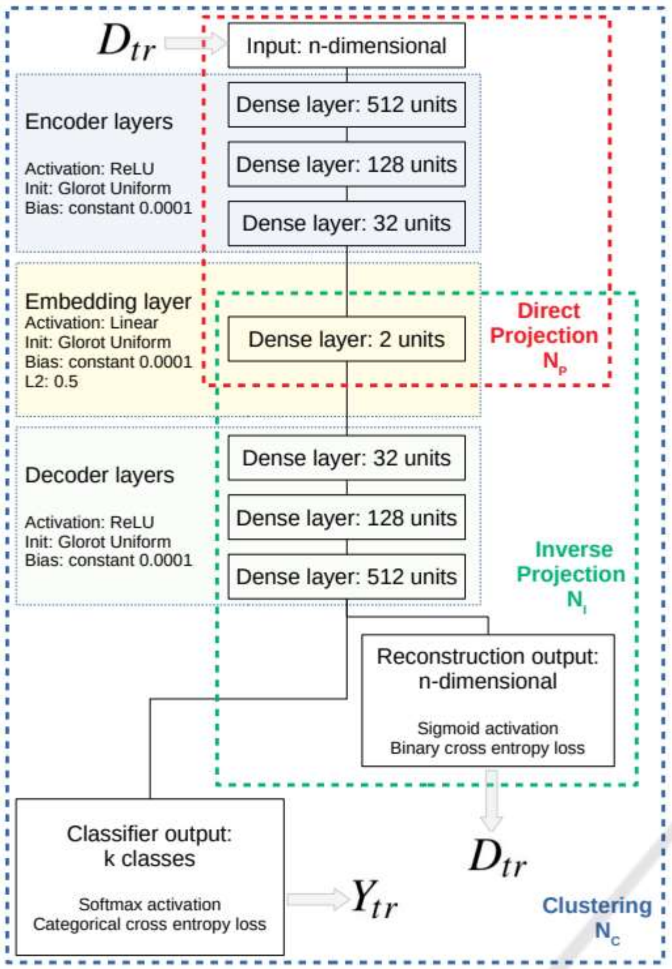
Pros:

- Easy to set-up, train and tune
- Easily parallelizable
- Out-of-sample capability
- Inverse mapping

Cons:

- Quality comparable to PCA

Method: Architecture

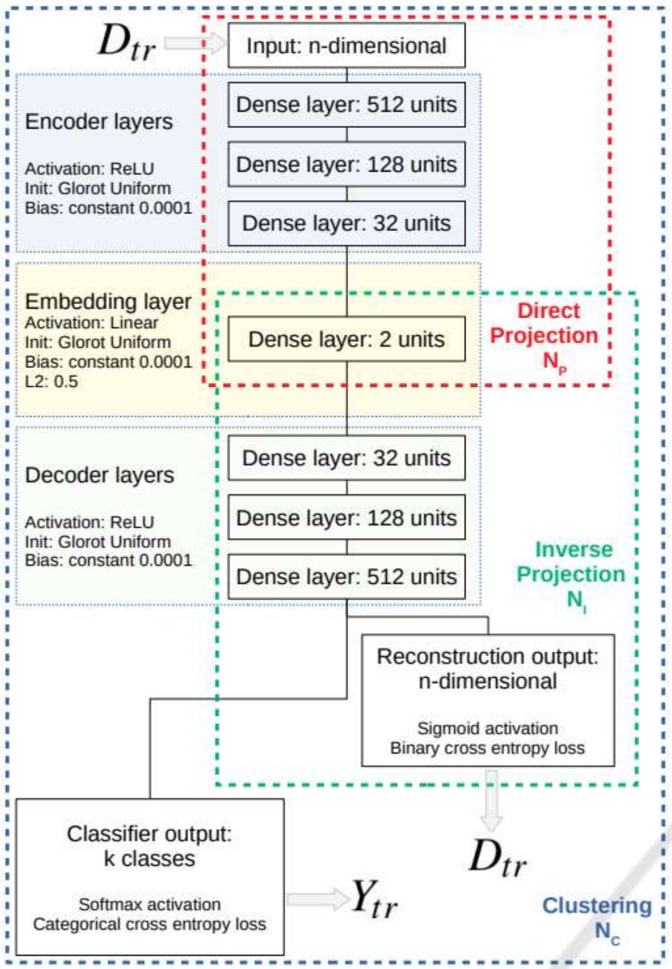


Key Idea

Autoencoders do not use neighborhood information during training while t-SNE and UMAP do that

Method: SSNP

- Dual optimization targets
- One reconstruction target
- A classification target
- Assigning labels with some clustering algorithms like K-means



Method: Training

1. **Label assignment:**

   Input: Clustering algorithm, Dtr

   Output: Ytr

   Clustering such as K-means

1. **Training:**

   Input: Dtr, Ytr

   Output: Trained network

   Stochastic gradient descent

   Joint optimization of classifier and reconstruction targets

3. **Assembly of final networks:**

   Input: Trained network

   Output: Np, Ni, Nc

   Dismantle trained network

   Construct final networks based on trained layers

4. **Inference:**

   Input: D→Np P(D)-->Ni

   D→Nc

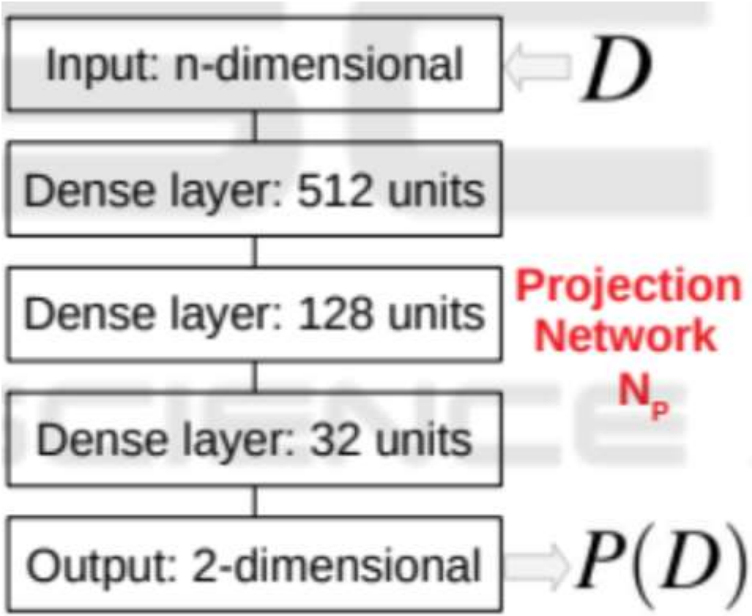
   Output: Np→P(D) Nt→D

   Nc→Y

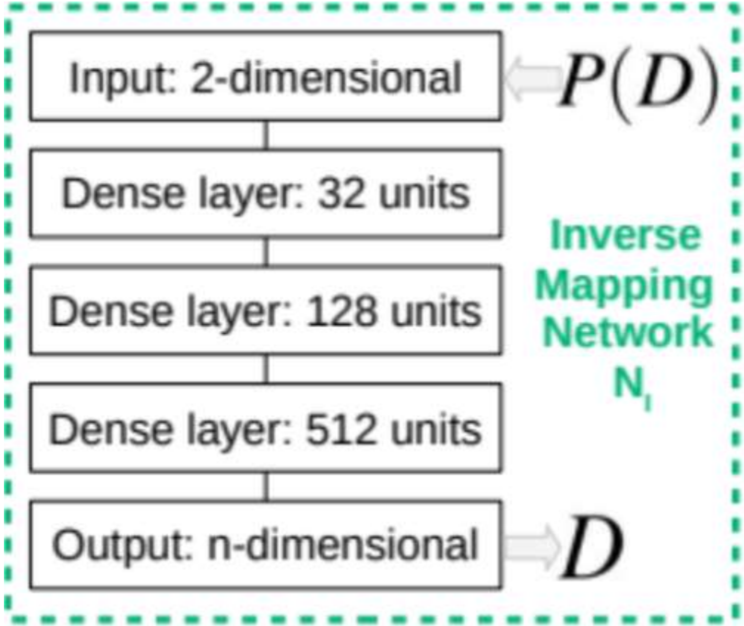
   Networks trained and ready to use for

   Direct projection, Inverse projection and Clustering

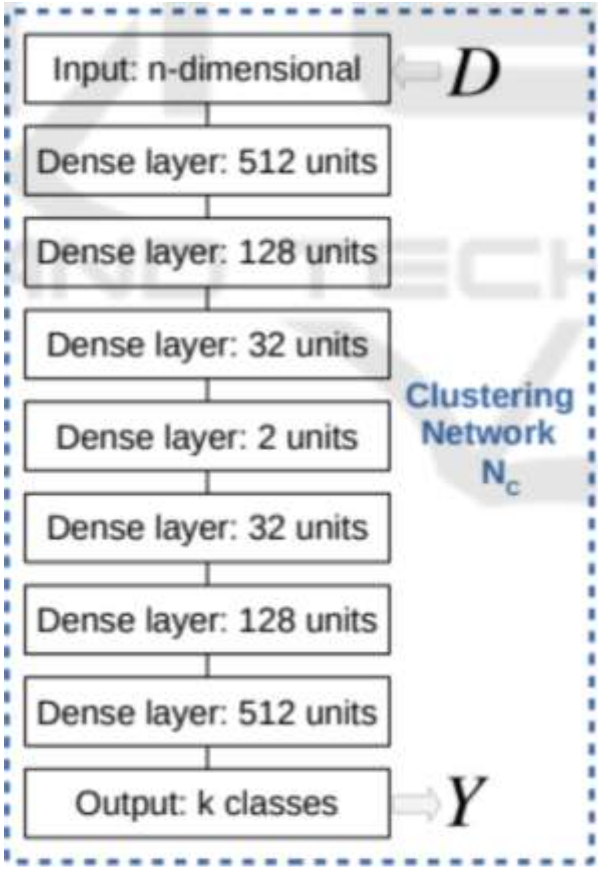
Projection Network



Inverse Mapping Network



Clustering Network



Results: Metrics

Metric	Definition	Range
Trustworthiness (T)	$1-\frac{2}{NK(2n-3K-1)}\sum_{i=1}^{N}\sum_{j\in U_i^{(K)}}(r(i,j)-K)$	$[0,\mathbf{1}]$
Continuity (C)	$1-\frac{2}{NK(2n-3K-1)}\sum_{i=1}^{N}\sum_{j\in V_i^{(K)}}(\hat{r}(i,j)-K)$	$[0,\mathbf{1}]$
Neighborhood hit (NH)	$\frac{1}{N}\sum_{\mathbf{y}\in P(D)}\frac{\mathbf{y}_k^l}{\mathbf{y}_k}$	$[0,\mathbf{1}]$
Shepard diagram correlation (R)	Spearman's ρ of $(\lVert\mathbf{x}_i-\mathbf{x}_j\rVert, \lVert P(\mathbf{x}_i)-P(\mathbf{x}_j)\rVert), 1\leq i\leq N, i\neq j$	$[0,\mathbf{1}]$

Results: Datasets

MNIST: 70K samples of handwritten digits from 0 to 9

Fashion MNIST: 70K samples of 10 types of pieces of clothing

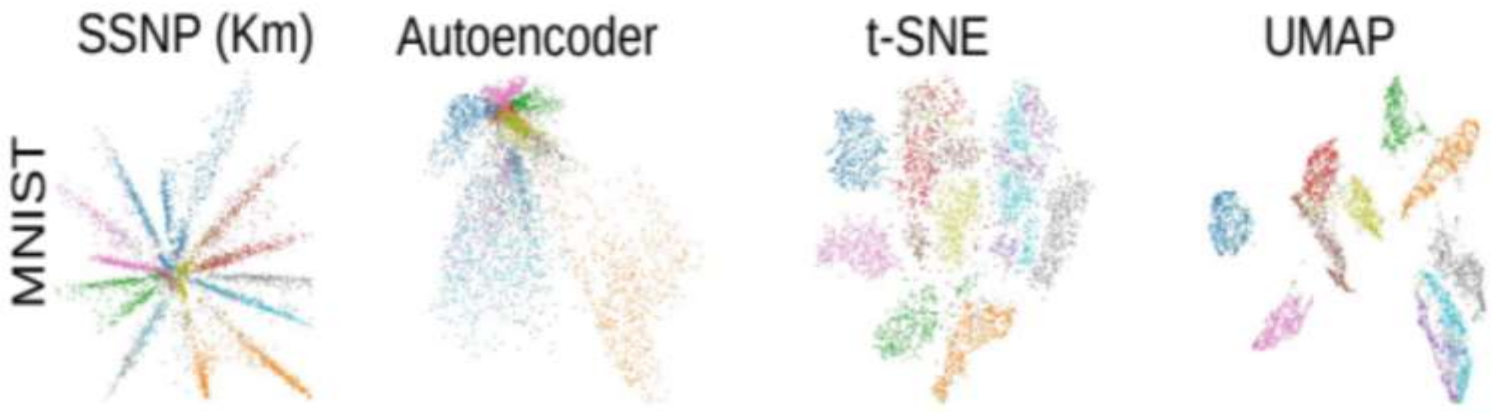
Human Activity Recognition (HAR): 10299 samples from 30 subjects performing activities of daily living used for human activity recognition, described with 561 dimensions.

Reuters Newswire Dataset: 8432 observations of news report documents, from which 5000 attributes were extracted using TF-IDF. This is a subset of the full dataset which contains data for the six most frequent classes only.

Results: Quality

Dataset	Method	T	C	R	NH
MNIST	SSNP-KMeans	0.8874095983	0.9232051427	0.3338461186	0.7699333333
	TSNE	0.9855493342	0.9721453884	0.4100766052	0.9450666667
	UMAP	0.9550900782	0.9737973771	0.3878280829	0.9166
	AE	0.8918473499	0.9019734101	0.09152170727	0.7152

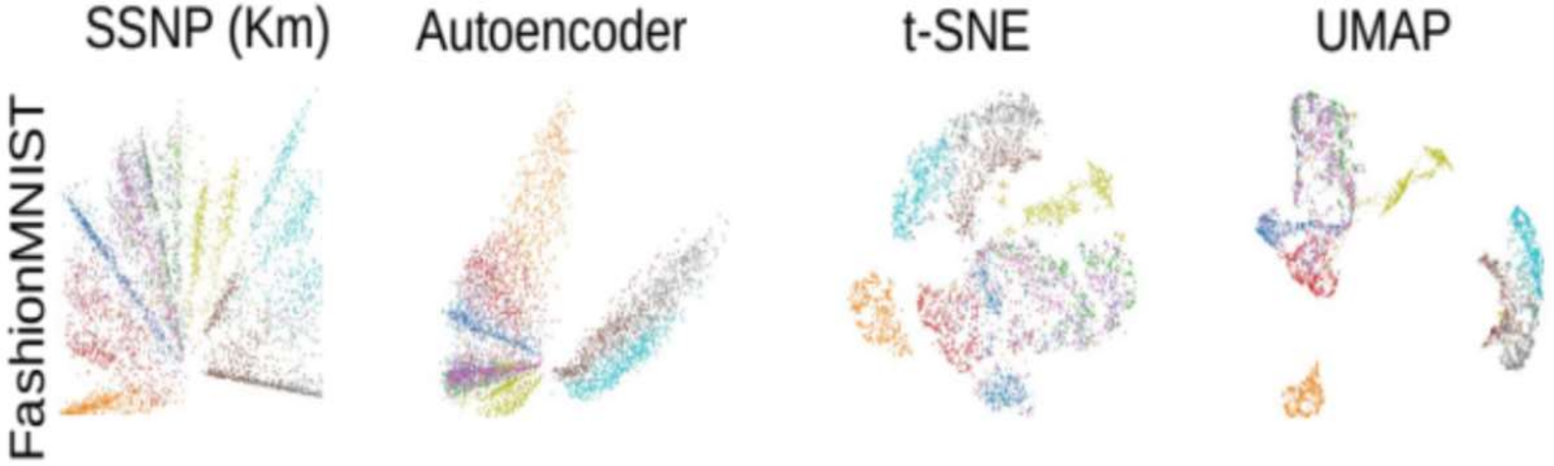
Results: Quality



Results: Quality

Dataset	Method	T	C	R	NH
FashionMNIST	SSNP-KMeans	0.9585190619	0.9791334135	0.6492234911	0.7411333333
	TSNE	0.9901974573	0.9871432924	0.6711292372	0.8442
	UMAP	0.9812796209	0.9878732698	0.634531252	0.8034666667
	AE	0.9600565816	0.9759209174	0.5087995078	0.7232

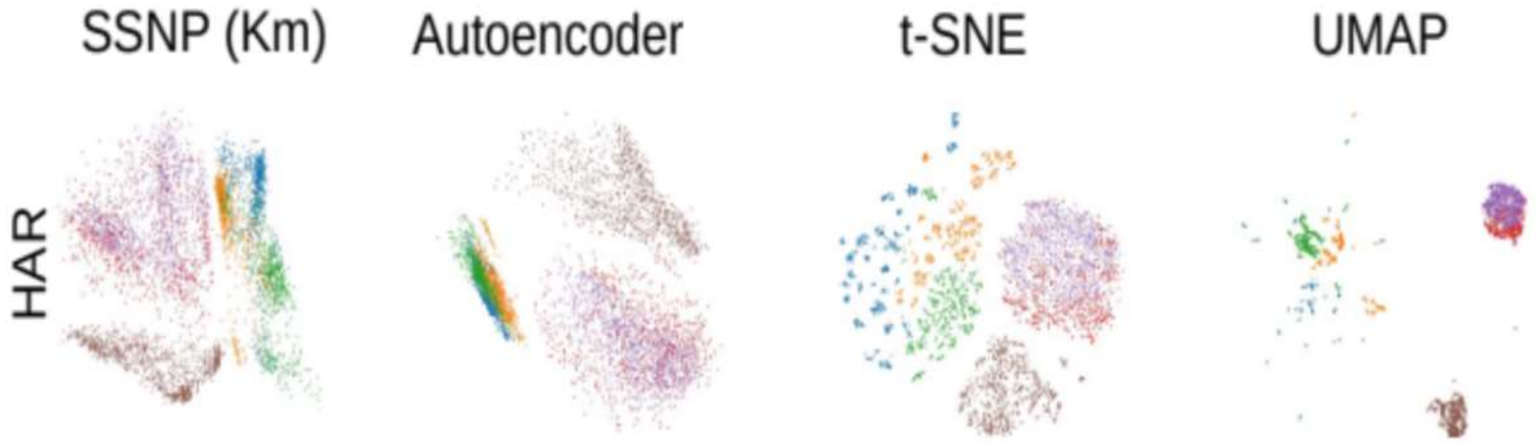
Results: Quality



Results: Quality

Dataset	Method	T	C	R	NH
HAR	SSNP-KMeans	0.9353182086	0.9664850271	0.6821554453	0.8336666667
	TSNE	0.9914620107	0.9855856141	0.5864212675	0.968
	UMAP	0.9788729319	0.9888910575	0.7904799456	0.9307333333
	AE	0.9348128053	0.9685248003	0.8334835666	0.7876

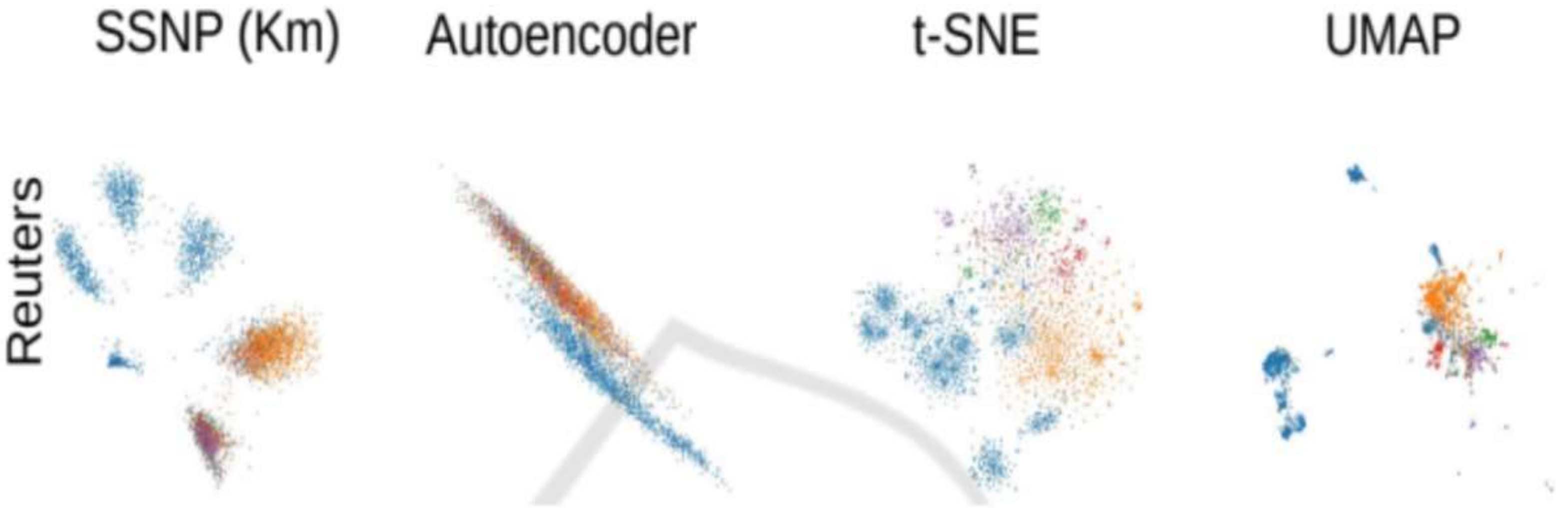
Results: Quality



Results: Quality

Dataset	Method	T	C	R	NH
Reuters	SSNP-KMeans	0.6090255934	0.7649792171	0.3347201725	0.7527333333
	TSNE	0.7411923031	0.910724806	0.02005786863	0.8399333333
	UMAP	0.6619760616	0.8551860379	-0.1077828313	0.7626
	AE	0.6179131976	0.748614867	-0.0061746199	0.7650666667

Results: Quality



Results: Computational Scalability

Method	Training time (s)
SSNP(Km)	20.478
AE	3.3734
UMAP	25.143
t-SNE	33.620

Results: Inverse Projection

	SSNP(KM)		Autoencoder	
Dataset	Train	Test	Train	Test
MNIST	0.47317	0.45441	0.43707	0.45441
FashionMNIST	0.32657	0.03355	0.29238	0.30534
HAR	0.007506	0.007594	0.006621	0.006717
Reuters	0.001294	0.001286	0.001301	0.001314

Results: Inverse Projection

Results: Clustering

	SSNP(KM)	
	Train	Test
MNIST	0.9386	0.789
FashionMNIST	0.909	0.84
HAR	0.8644	0.857
Reuters	0.9976	0.951

Conclusion

- New dimensionality reduction technique called SSNP
- Addresses all characteristics required by a DR method
- Produces projections with better visual separation than autoencoders
- Handles large datasets easily and quickly
- Can handle any type of data with out-of-sample support
- Inverse projection

References

Amorim, E., Brazil, E. V., Daniels, J., Joia, P., Nonato, L. G., and Sousa, M. C. (2012). iLAMP: Exploring high-dimensional spacing through backward multidimensional projection. In Proc. IEEE VAST, pages 53– 62.

Anguita, D., Ghio, A., Oneto, L., Parra, X., and ReyesOrtiz, J. L. (2012). Human activity recognition on smartphones using a multiclass hardware-friendly support vector machine. In Proc. Intl. Workshop on Ambient Assisted Living, pages 216–223. Springer.

Becker, M., Lippel, J., Stuhlsatz, A., and Zielke, T. (2020). Robust dimensionality reduction for data visualization with deep neural networks. Graphical Models, 108:101060.

References

Becker, R., Cleveland, W., and Shyu, M. (1996). The visual design and control of the trellis display. Journal of Computational and Graphical Statistics, 5(2):123–155.

Chan, D., Rao, R., Huang, F., and Canny, J. (2018). T-SNECUDA: GPU-accelerated t-SNE and its applications to modern data. In Proc. SBAC-PAD, pages 330–338.

Cunningham, J. and Ghahramani, Z. (2015). Linear dimensionality reduction: Survey, insights, and generalizations. JMLR, 16:2859–2900.

Donoho, D. L. and Grimes, C. (2003). Hessian eigenmaps: Locally linear embedding techniques for high dimensional data. Proc Natl Acad Sci, 100(10):5591– 5596.

Thank You