# Understanding Dimension Reduction Algorithms

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# Dimension reduction (DR) algorithms

Input: high-dimensional data

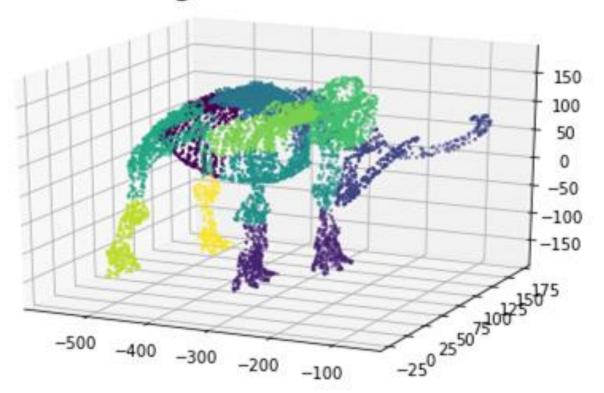
Output: low-dimensional data that preserves...

- the graph structure?
- local neighborhoods?
- global structure?

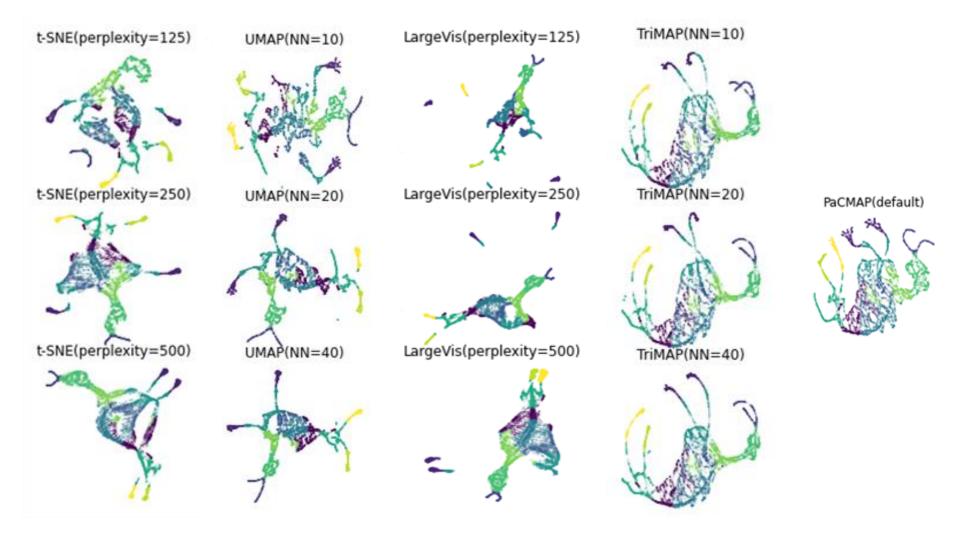
Previous successful DR algorithms: t-SNE, UMAP, Largevis, TriMAP, ...

Our new algorithm: PaCMAP

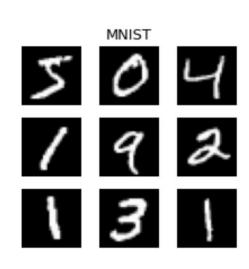
# Original Mammoth

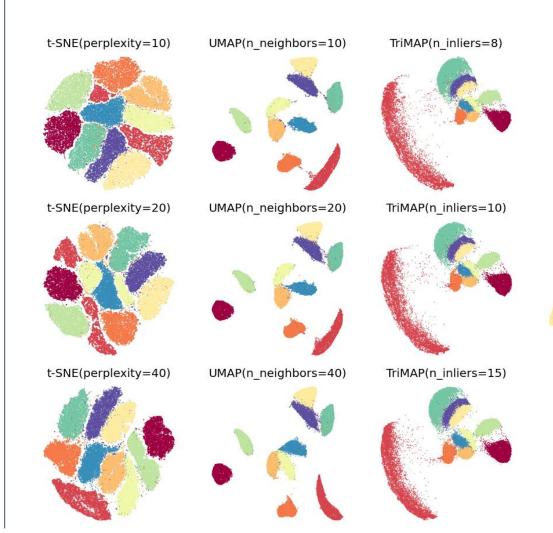


Task: 3d to 2d. Global structure is important here!



# MNIST dataset (handwritten digit image)





**PaCMAP** 

Algorithm	Graph component	Loss function				
t-SNE	Edges $(i, j)$	Loss <sub>i,j</sub> <sup>t-SNE</sup> = $p_{ij} \log \frac{p_{ij}}{q_{ij}}$ , where $q_{ij} = \frac{\left(1 + \ \mathbf{y}_i - \mathbf{y}_j\ ^2\right)^{-1}}{\sum_{k \neq l} (1 + \ \mathbf{y}_k - y_l\ ^2)^{-1}}$				
UMAP	Edges $(i, j)$	$\operatorname{Loss}_{i,j}^{\operatorname{UMAP}} = \begin{cases} \bar{w}_{i,j} \log \left( 1 + a \left( \ \mathbf{y}_i - \mathbf{y}_j\ _2^2 \right)^b \right)^{-1} & i, j \text{ neighbo} \\ \left( 1 - \bar{w}_{i,j} \right) \log \left( 1 - \left( 1 + a \left( \ \mathbf{y}_i - \mathbf{y}_j\ _2^2 \right)^b \right)^{-1} \right) & \operatorname{Otherwise} \end{cases}$	ors			
TriMAP	Triplets $(i, j, k)$ where Distance <sub>i,j</sub> $\leq$ Distance <sub>i,k</sub>	$\operatorname{Loss}^{\operatorname{TM}}_{i,j,k} = \omega_{i,j,k} \frac{s(\mathbf{y}_i,\mathbf{y}_k)}{s(\mathbf{y}_i,\mathbf{y}_j) + s(\mathbf{y}_i,\mathbf{y}_k)}, \text{ where } s(\mathbf{y}_i,\mathbf{y}_j) = \left(1 + \ \mathbf{y}_i - \mathbf{y}_j\ ^2\right)^{-1}$				

t-SNE (van der Maaten and Hinton, 2008), UMAP (McInnes et al., 2018), TriMAP (Amid & Warmuth, 2019)

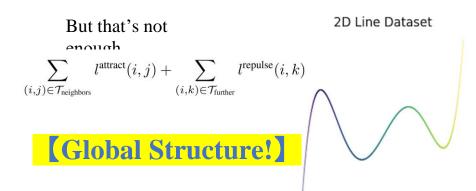
# What elements of these algorithms are important?

## What we knew before:

## Certain properties of the loss function are important:

- Attraction: neighbors should be attracted. But not too close! (Crowding)
- Repulsion: farther points in original space should be far in low-dim space.

**[Local Structure!]** 



After a huge amount of experimentation, we found that:

#### For local structure:

• Certain specific properties of the loss function are important.

- We must have forces on non-neighbors.
- The choice of which graph components to preserve is important.

Algo	rithm	Graph component	Loss function				
t-S	NE	Edges $(i, j)$	Loss <sub>i,j</sub> <sup>t-SNE</sup> = $p_{ij} \log \frac{p_{ij}}{q_{ij}}$ , where $q_{ij} = \frac{\left(1 + \ \mathbf{y}_i - \mathbf{y}_j\ ^2\right)^{-1}}{\sum_{k \neq l} (1 + \ \mathbf{y}_k - y_l\ ^2)^{-1}}$				
UM	IAP	Edges $(i, j)$	$\operatorname{Loss}_{i,j}^{\operatorname{UMAP}} = \begin{cases} \bar{w}_{i,j} \log \left( 1 + a \left( \ \mathbf{y}_i - \mathbf{y}_j\ _2^2 \right)^b \right)^{-1} & i, j \text{ neighbors} \\ \left( 1 - \bar{w}_{i,j} \right) \log \left( 1 - \left( 1 + a \left( \ \mathbf{y}_i - \mathbf{y}_j\ _2^2 \right)^b \right)^{-1} \right) & \operatorname{Otherwise} \end{cases}$				
TriN	ЛАР	Triplets $(i, j, k)$ where Distance <sub>i,j</sub> $\leq$ Distance <sub>i,k</sub>	$\operatorname{Loss}^{\operatorname{TM}}_{i,j,k} = \omega_{i,j,k} \frac{s(\mathbf{y}_i,\mathbf{y}_k)}{s(\mathbf{y}_i,\mathbf{y}_j) + s(\mathbf{y}_i,\mathbf{y}_k)}, \text{ where } s(\mathbf{y}_i,\mathbf{y}_j) = \left(1 + \ \mathbf{y}_i - \mathbf{y}_j\ ^2\right)^{-1}$				

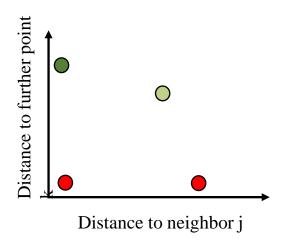
t-SNE (van der Maaten and Hinton, 2008), UMAP (McInnes et al., 2018), TriMAP (Amid & Warmuth, 2019)

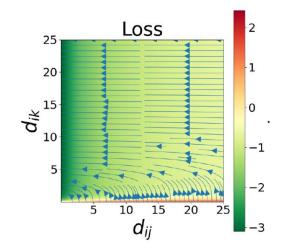
#### For local structure:

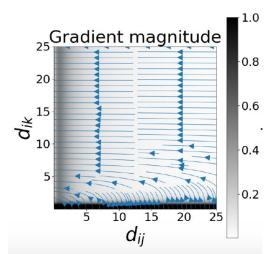
Certain specific properties of the loss function are important.

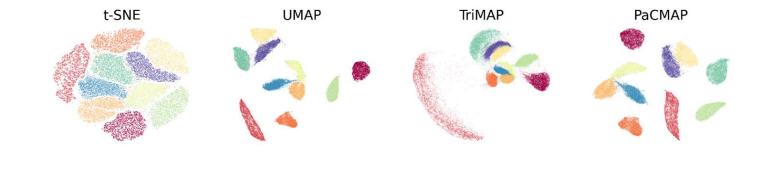
# The "rainbow" plot

Triplet i, j (neighbor), k (further)



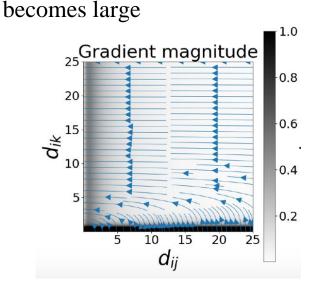


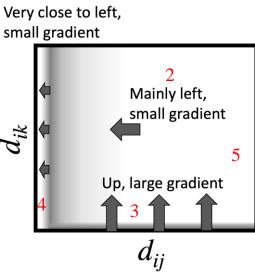


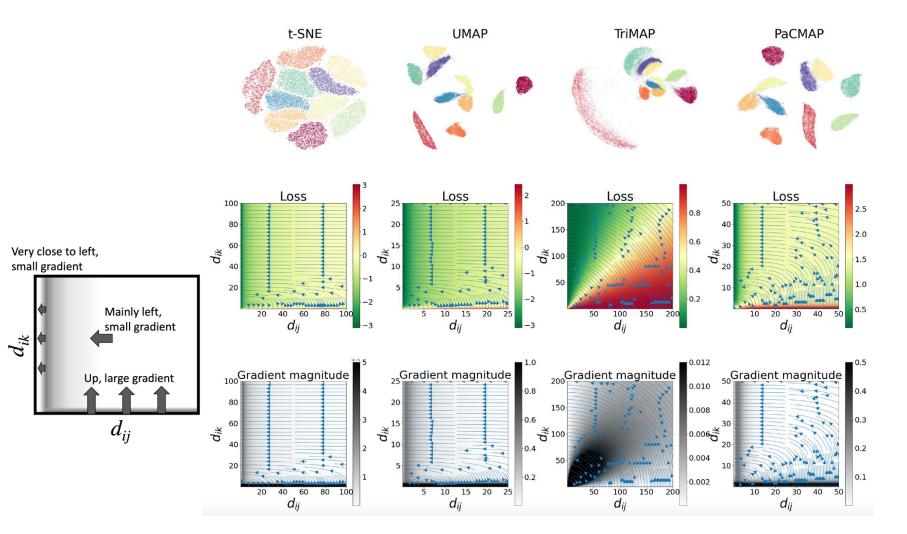


# Principles for a good loss for DR

- 1) Monotonicity: pull neighbors closer, push farther points away (go left, go up)
- 2) Except along the bottom, gradient should go mainly to the left (broadly attract neighbors, further points are far enough), sufficient attraction
- 3) Along bottom, gradient goes mainly up (further point is too close) with large gradient
- 4) Along vertical axis, small magnitude (neighbor is close enough)
- 5) Weak pull on far neighbors: gradients should become small as distance to neighbor j







$$Loss = log(1 + exp(\frac{d_{ij}^2 - d_{ik}^2}{10})$$

$$Loss = \frac{d_{ij}^2 + 1}{d_{ik}^2 + 1}$$

$$Loss = -\frac{d_{ik}^2 + 1}{d_{ii}^2 + 1}$$

$$Loss = log(1 + exp(d_{ij}^2) + exp(-d_{ik}^2))$$

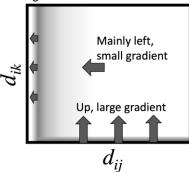












Too much repulsion Insufficient attraction

No gradient on repulsion

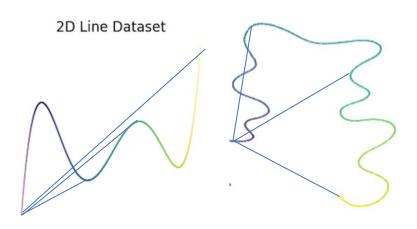
Insufficient local attraction

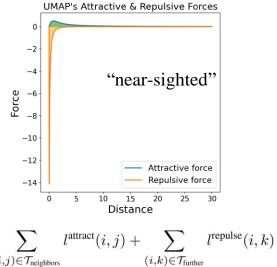
After a huge amount of experimentation, we found that:

#### For local structure:

• Certain specific properties of the loss function are important.

- We must have forces on non-neighbors.
- The choice of which graph components to preserve is important.





$$\sum_{(i,j) \in \mathcal{T}_{ ext{neighbors}}} l^{ ext{attract}}(i,j) + \sum_{(i,k) \in \mathcal{T}_{ ext{further}}} l^{ ext{repulse}}(i,k)$$

- We must have forces on non-neighbors.
- The choice of which graph components to preserve is important.

MN: mid-near FP: further point

$$Loss^{PaCMAP} = w_{neighbors}Loss_{neighbors} + w_{MN}Loss_{MN} + w_{FP}Loss_{FP}$$

$$Loss_{neighbors} = \frac{\tilde{d}_{ij}}{10 + \tilde{d}_{ij}}, \quad Loss_{MN} = \frac{\tilde{d}_{ik}}{10000 + \tilde{d}_{ik}}, \quad Loss_{FP} = \frac{1}{1 + \tilde{d}_{il}}$$

attractive

mild attractive

Neighbors: Mid-near pairs: Further points: repulsive

- We must have forces on non-neighbors.
- The choice of which graph components to preserve is important.

$$Loss^{PaCMAP} = w_{neighbors} Loss_{neighbors} + w_{MN} Loss_{MN} + w_{FP} Loss_{FP}$$

$$\label{eq:Loss_neighbors} \begin{split} \text{Loss}_{\text{neighbors}} &= \frac{\tilde{d}_{ij}}{10 + \tilde{d}_{ij}}, \quad \text{Loss}_{MN} = \frac{\tilde{d}_{ik}}{10000 + \tilde{d}_{ik}}, \quad \text{Loss}_{FP} = \frac{1}{1 + \tilde{d}_{il}} \\ \text{Neighbors:} & \quad \text{Mid-near pairs:} & \quad \text{Further points:} \\ \text{attractive} & \quad \text{mild attractive} & \quad \text{repulsive} \end{split}$$

## The weights change on a schedule:

Period 1:  $w_{\text{neighbors}}$  is medium,  $w_{MN}$  is huge,  $w_{FP}$  is medium

Period 2:  $w_{\text{neighbors}}$  is large,  $w_{MN}$  is small,  $w_{FP}$  is medium

Period 3:  $w_{\text{neighbors}}$  is medium,  $w_{MN}$  is 0,  $w_{FP}$  is medium



 $0.699 \pm 0.007$ 

 $0.718 \pm 0.005$ 

 $0.665 \pm 0.002$ 

 $0.866 \pm 0.010$ 

 $0.872 \pm 0.003$ 

 $0.666 \pm 0.003$ 

 $0.727 \pm 0.001$ 

 $0.619 \pm 0.001$ 

 $0.741 \pm 0.002$ 

 $0.894 \pm 0.005$ 

 $0.752 \pm 0.002$ 

DATASET (SIZE)	BASELINE	T-SNE	LARGEVIS	UMAP	TRIMAP	PACMAP
COIL-20 (1.4K) COIL-100 (7.2K)	0.972 0.989	$0.909 \pm 0.015$ $0.911 \pm 0.004$	$0.799 \pm 0.020$ $0.707 \pm 0.014$	$0.844 \pm 0.004$ $0.879 \pm 0.007$	$0.778 \pm 0.010$ $0.737 \pm 0.019$	$0.942 \pm 0.009 \\ 0.933 \pm 0.009$
USPS (9K)	0.949	$0.959 \pm 0.002$	$0.957 \pm 0.001$	$0.956 \pm 0.002$	$0.946 \pm 0.001$	$0.958 \pm 0.001$

SVM accuracy (measures local structure preservation)

TASET (SIZE) BASELINE 1-SNE LARGEVIS UMAP TRIMAP

IL-20 (1.4K) 0.972 0.909 
$$\pm$$
 0.015 0.799  $\pm$  0.020 0.844  $\pm$  0.004 0.778  $\pm$  0.010

IL-100 (7.2K) 0.989 0.911  $\pm$  0.004 0.707  $\pm$  0.014 0.879  $\pm$  0.007 0.737  $\pm$  0.019

PS (9k) 0.940 0.950  $\pm$  0.002 0.957  $\pm$  0.001 0.956  $\pm$  0.002 0.946  $\pm$  0.001

 $0.698 \pm 0.016$ 

 $0.577 \pm 0.012$ 

 $0.654 \pm 0.013$ 

 $0.722 \pm 0.045$ 

 $0.701 \pm 0.038$ 

 $0.645 \pm 0.002$ 

 $0.715 \pm 0.002$ 

 $0.600 \pm 0.007$ 

 $0.679 \pm 0.019$ 

COIL-20 (1.4K)

USPS (9K)

COIL-100 (7.2K)

MAMMOTH (10K)

MNIST (70K)

F-MNIST (70K)

KDD CUP99 (4M)

20Newsgroups (18K)

S-CURVE WITH HOLE (9.5K)

Mouse scrna-seq (20K)

FLOW CYTOMETRY (3M)

COIL-20 (1.4K)
 
$$0.972$$
 $0.909 \pm 0.015$ 
 $0.799 \pm 0.020$ 
 $0.844 \pm 0.004$ 
 $0.778 \pm 0.010$ 
 $0.942 \pm 0.009$ 

 COIL-100 (7.2K)
  $0.989$ 
 $0.911 \pm 0.004$ 
 $0.707 \pm 0.014$ 
 $0.879 \pm 0.007$ 
 $0.737 \pm 0.019$ 
 $0.933 \pm 0.009$ 

 USPS (9K)
  $0.949$ 
 $0.959 \pm 0.002$ 
 $0.957 \pm 0.001$ 
 $0.956 \pm 0.002$ 
 $0.946 \pm 0.001$ 
 $0.958 \pm 0.001$ 

 MAMMOTH (10K)
  $0.961$ 
 $0.927 \pm 0.009$ 
 $0.923 \pm 0.011$ 
 $0.941 \pm 0.003$ 
 $0.900 \pm 0.004$ 
 $0.933 \pm 0.004$ 

 20Name of power (18k)
  $0.702$ 
 $0.425 \pm 0.014$ 
 $0.444 \pm 0.012$ 
 $0.421 \pm 0.003$ 
 $0.900 \pm 0.004$ 
 $0.447 \pm 0.006$ 

OIL-100 (7.2K)	0.989	$0.911 \pm 0.004$	$0.707 \pm 0.014$	$0.879 \pm 0.007$	$0.737 \pm 0.019$	$0.933 \pm$
SPS (9K)	0.949	$0.959 \pm 0.002$	$0.957 \pm 0.001$	$0.956 \pm 0.002$	$0.946 \pm 0.001$	0.958 ±
АММОТН (10K)	0.961	$0.927 \pm 0.009$	$0.923 \pm 0.011$	$0.941 \pm 0.003$	$0.900 \pm 0.004$	0.933 =
NEWSGROUPS (18K)	0.792	$0.435 \pm 0.014$	$0.444 \pm 0.012$	$0.431 \pm 0.013$	$0.410 \pm 0.007$	<b>0.447</b> ±
NIST (70K)	0.926	$0.967 \pm 0.002$	$0.965 \pm 0.004$	$0.970 \pm 0.001$	$0.960 \pm 0.001$	$0.974 \pm$

20NEWSGROUPS (18K) MNIST (70K) F-MNIST (70K)	0.792 0.926 0.854	$0.435 \pm 0.014$ $0.967 \pm 0.002$ $0.754 \pm 0.003$	$0.444 \pm 0.012 \\ 0.965 \pm 0.004 \\ 0.748 \pm 0.003$	$0.431 \pm 0.013$ $0.970 \pm 0.001$ $0.742 \pm 0.003$	$0.410 \pm 0.007$ $0.960 \pm 0.001$ $0.729 \pm 0.001$	$0.447 \pm 0.006$ $0.974 \pm 0.001$ $0.752 \pm 0.004$	
Random triplet accuracy (measures global structure preservation)							
DATASET (SIZE)		T-SNE	LargeVis	UMAP	TRIMAP	PACMAP	

 $0.649 \pm 0.014$ 

 $0.568 \pm 0.011$ 

 $0.669 \pm 0.002$ 

 $0.800 \pm 0.013$ 

 $0.816 \pm 0.001$ 

 $0.664 \pm 0.002$ 

 $0.727 \pm 0.002$ 

 $0.614 \pm 0.001$ 

 $0.740 \pm 0.001$ 

t-SNE version: opt-SNE (Belkina et al., 2019) built on Multi-core t-SNE (Ulyanov et al., 2016)

 $0.659 \pm 0.006$ 

 $0.633 \pm 0.002$ 

 $0.640 \pm 0.002$ 

 $0.838 \pm 0.004$ 

 $0.874 \pm 0.001$ 

 $0.704 \pm 0.002$ 

 $0.728 \pm 0.001$ 

 $0.600 \pm 0.001$ 

 $0.777 \pm 0.001$ 

 $0.857 \pm 0.001$ 

 $0.660 \pm 0.007$ 

 $0.735 \pm 0.011$ 

 $0.630 \pm 0.021$ 

 $0.668 \pm 0.011$ 

 $0.834 \pm 0.041$ 

 $0.766 \pm 0.024$ 

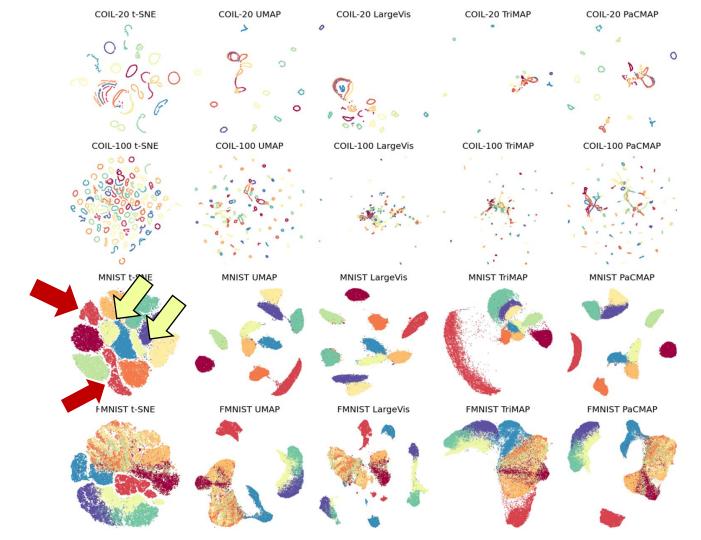
 $0.632 \pm 0.001$ 

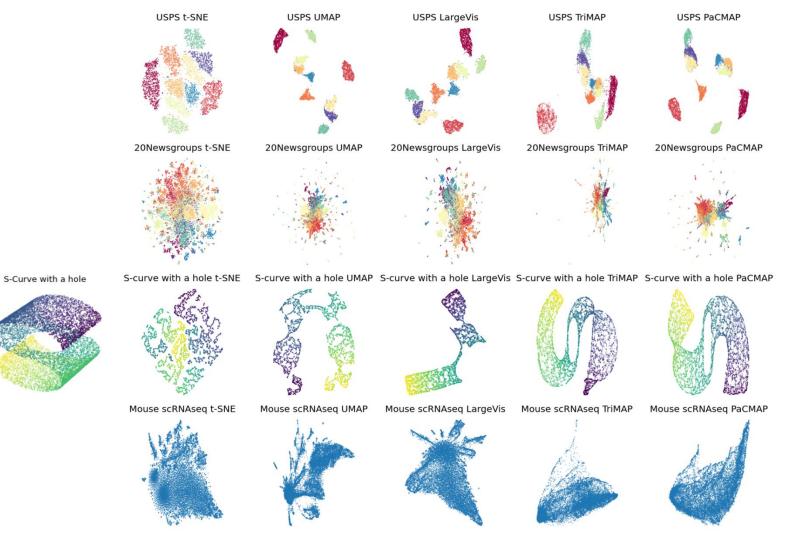
 $0.719 \pm 0.003$ 

 $0.601 \pm 0.007$ 

 $0.657 \pm 0.011$ 

(Ran out of memory or time, >24 hrs)





# Thanks!