UMAP

What is Dimension reduction?

Dimension reduction, is the transformation of data from a high-dimensional space into a low-dimensional space so that the low-dimensional representation retains some **meaningful properties** of the original data

Dimension reduction algorithms tend to fall into two categories;

•those that seek to preserve the pairwise distance structure amongst all the data samples.

Eg. PCA, MDS, and Sammon mapping.

•those that favor the preservation of local distances over global distance.

Eg. t-SNE, Isomap, LargeVis, Laplacian eigenmaps, UMAP

Why not PCA?

For **visualization**, our humans could only visualize 2 or 3-dimensional plot. Since PCA preserves the global picture of the dataset, if the dataset is complex, it normally remains complex in 2 or 3 PCs space.

Three steps of UMAP:

- 1. Constructs a high dimensional graph
- 2. Constructs a low dimensional graph
- 3. Optimizes the low-dimensional graph to be high dimensional one as similar as possible

Algorithm 1 UMAP algorithm

function UMAP(X, n, d, min-dist, n-epochs)

(1)

Construct the relevant weighted graph

for all $x \in X$ do

 $fs\text{-set}[x] \leftarrow LocalFuzzySimplicialSet(X, x, n)$

- (2)
- # Perform optimization of the graph layout
- $Y \leftarrow \text{SpectralEmbedding(top-rep, } d)$
- Y ← OptimizeEmbedding(top-rep, Y, min-dist, n-epochs)

return Y

1. Constructs a high dimensional graph

What is the desired graph? A particular weighted k-neighbour Graph

With neighbors and distance (weight)

How to construct this graph?

- ullet Let $X=\{x_1,...,x_N\}$ be the input dataset with metric d
- ullet Find set of nearest k-neighbours $\{x_{i_1},...,x_{i_k}\}$ of x_i under metric d
- · Weight function:

$$w((x_i, x_{i_j})) = \exp\left(\frac{-\max(0, d(x_i, x_{i_j}) - \rho_i)}{\sigma_i}\right)$$

- $d_{\mathbb{R}_N}(x_i, x_{i_j})$ is the Euclidean distance in \mathbb{R}^N
- $ho_i=\min\{d(x_i,x_{i_j})\mid 1\leq j\leq k, d(x_i,x_{i_j})>0\}$ ensures that x i connects to at least one other data point with an edge of weight 1
- normalisation factor σ_i such that $\sum_{j=1}^k \exp\left(\frac{-\max(0,d(x_i,x_{i_j})-\rho_i)}{\sigma_i}\right) = \log_2(k)$

What is the property of the final umap high dimentional graph?

1.Explore final weighted graph







- · Undirected graph
- · The largest weight is always 1
- . Sum of weights is no longer log₂(k)
- New sum ≥ log₂(k)
- Each point is now connected to at least k-1 other points

0.8	•
<	1
1	b

	Α	В	С
Α	0	1	0.8
В	1	0	1
С	0.8	1	0

why?

Approximating underlying manifold

- * Assume D is uniformly distributed on the manifold M $D \in \mathbb{R}^N$
 - Then a ball of fixed volume V on M should contain the same number of points
 - Conversely a ball centred on point x that contains its k-nearest neighbours has fixed volume regardless of the choice of x



	Α	В	С
Α	0	1	0.8
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 \mathbb{R}^N is the high dimensional space

2. Standard steps of optimization:

Sample high and low dimension pairs

Calculate distances of sampled pairs in both high and low dimensions

Calculate the cost of dis-similarity of distances

Minimize the cost

Two different steps in the UMAP to do optimization.

How to Sample?

UMAP selects a pair of points within a cluster proportionally to their high-dimensional weight P(ab) > P(ac)

How to Calculate distances in two dimensions?

- High dimension: weighted graph
 Low dimension: Some form of Euclidean distance

How to calculate the cost of dis-similarity?

- Optimisation problem of finding the low dimensional representation
- $w_h(e)$ weight of edge e in high dimensional case
- + $w_{\rm T}(e)$ weight in low dimensional case
- Cross entropy



Take limits as $\underline{w}_k > 1$: \underline{w}_i will be large to minimise the first term

we randomly sample potential edges and assume them to be a negative example (i.e. with weight in high dimension equals to 0)

How to Calculate distances in two dimensions?

- High dimension: weighted graph
 Low dimension: Euclidean distance

How to calculate the cost of dis-similarity?

- · Optimisation problem of finding the low dimensional representation
- · Cross entropy

$$(1-w_h(e))\log \left(\frac{1-w_h(e)}{1-w_l(e)}\right)$$

Take limits as w_b -> 0: w_c is forced to be small to minimise the second