T-SNE (t-distb stochastic Neighborhood Embedding)

15.1 What is t-SNE

→ state of the art/best dim-red ⟶ Visualization.

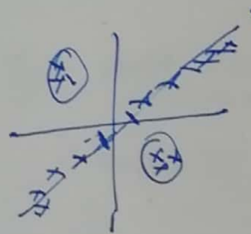
→ PCA basic; old

→ multidimensional scaling, Sammon mapping, Graph based technique

→ T-SNE ÷ 2008 → 11 years old technique.

$d\text{-dim} \xrightarrow{t\text{-SNE}} \boxed{2d}$

→ fundamental diff b/w t-SNE & PCA

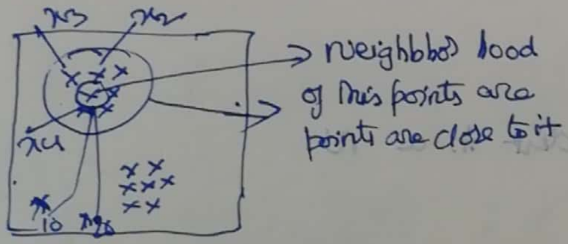


PCA : Try to preserve global shape/structure of data
doesn't care about local structure

TSNE ÷ Preserve local structure

1.5.2 Neighborhood of a point, Embedding

d-dim: (high)

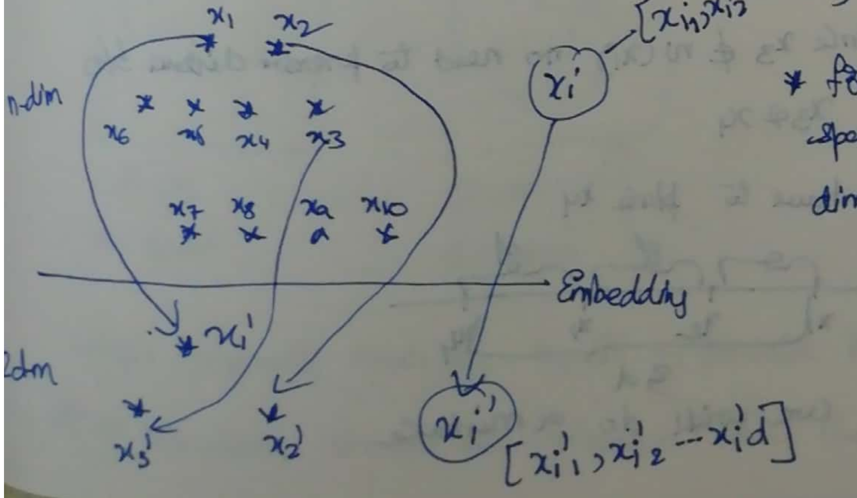


$N(x_i)$: {x_j, such that x_i & x_j are geometrically close}

$||x_i - x_j||^2 = dist^2$

$N(x_1) = \{x_2, x_3, x_4\}$; does not contain x_{10} & x_{20}.

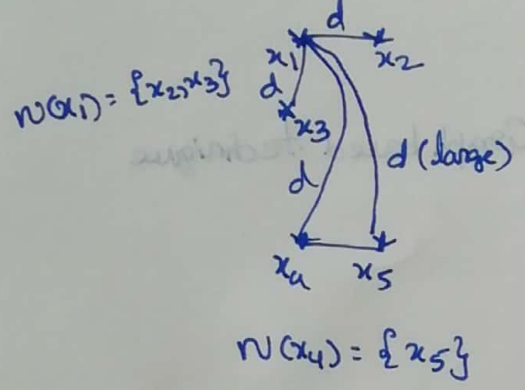
Embedding



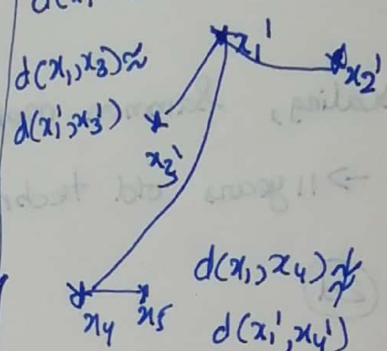
* for Every point in high dimensional space finding a point in low dimensional space is called Embedding

15.3 Geometric intuition of t-SNE

d-dim $x_i \in \mathbb{R}^d$ | 2-dim $x_i \in \mathbb{R}^2$



$d(x_1, x_2) \approx d(x_1', x_2')$



$d(x_1, x_3) \approx d(x_1', x_3')$

$d(x_1, x_4) \not\approx d(x_1', x_4')$

$d(x_4, x_5) = d(x_4', x_5')$

* preserving the dist in neighborhood & not preserving the distance b/w the points which are outside neighborhood (x_4, x_5)

→ neighborhood preserving Embedding

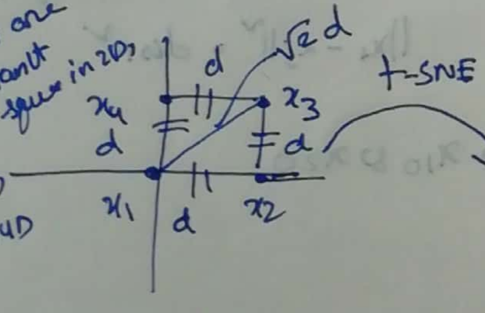
mathematical formulation

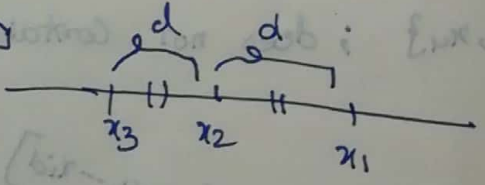
→ fairly advanced (2008)

15.4 Crowding Problem

t-SNE :- Tries to preserve dist in a N

All points are equidistant if formed a square in 2D, Cube in 3D, hypercube in 4D

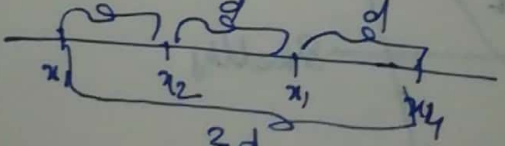




2D

* Since $x_3 \notin N(x_1)$ no need to preserve distance b/w x_3 & x_4

* we have to place x_4



* we even we have placed x_4 we will do a mistake

* Sometimes; It is impossible to preserve dist in all the neighbourhoods (N)

this is called Crowding problem.

15.5 How to apply t-SNE and interpret its output

https://distill.pub/2016/misread-tsne/

d-dim $\longrightarrow$ d'dim

$d = d' = 2$

→ T-SNE is an iterative algorithm. and reach a point where a clusters are no-more moving

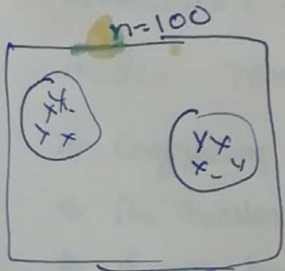
Two most imp parameters

1) Perplexity ② step-size (# of iterations) as high the better.

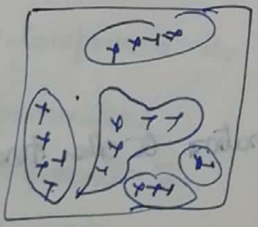
$\downarrow$

# of neighbours distance that we are going to preserve.

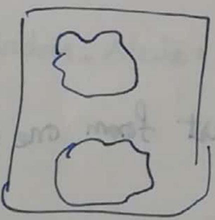
If my perplexity 2, 5, 30, 50, 100



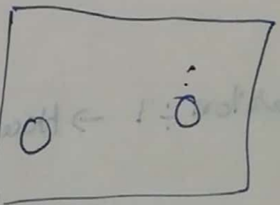
Original



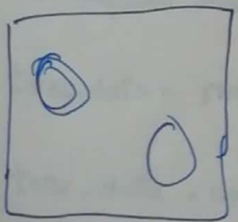
Perplexity=2
step = 5000



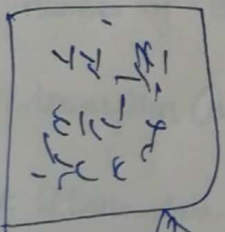
P=5
S=5000



P=30
S=5000



P=50
S=5000



P=100
S=5,000

when perplexity matches the # of points This is a mess

# of iterations should be increased till the shape is stabilized

t-SNE
$\hookrightarrow$ Stochastic
$\uparrow$
Probability

* Run t-SNE on the same dataset with same parameter we will be a slightly different results

Deterministic algo ÷ same results for any run
Stochastic algo ÷ slightly different result Every time

* Expands dense clusters
* Shrinks sparse clusters

} Drawbacks

Steps

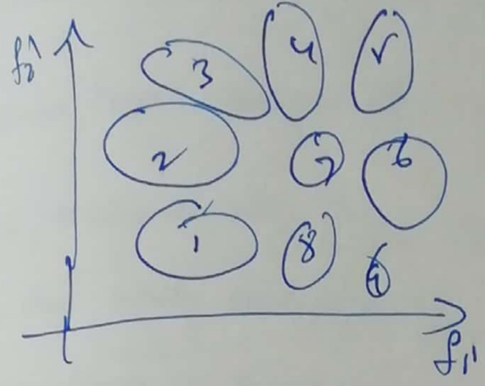
① Run step/iteration till shape stabilizes.
② Perplexity $\boxed{2 \leq P \leq n}$
③ re-run t-sne multiple times

* Epsilon ÷ 1 → How fast from one iteration to other iteration.

15.6 t-SNE on MNIST

colah.github.io/posts/2014-10-~~Visualizing~~ Visualizing-MNIST/

784 dim → 2 dim



* Cannot interpret cluster sizes (or) inter cluster distances

15.7 Code Example of t-SNE

t-SNE using Scikit Learn

```
from sklearn.manifold import TSNE
# Picking the top 1000 points as TSNE takes a lot of time for 15K points
 data_1000 = standardized_data[0:1000,:]
 labels_1000 = labels[0:1000]
 model = TSNE(n_components=2, random_state=0)
 # Configuring the parameters
 # the number of components = 2
 # default perplexity = 30
 # default learning rate = 200
 # default Maximum number of iterations for the optimization = 1000
tsne_data = model.fit_transform(data_1000)
tsne_data = np.vstack((tsne_data.T, labels_1000)).T
tsne_df = pd.DataFrame(data=tsne_data, columns=('Dim1', 'Dim2', 'label'))
# Plotting the result of tsne
sn.FacetGrid(tsne_df, hue='label', size=6).map(plt.scatter, 'Dim1', 'Dim2')
plt.show()
```

Try

n_components = 2, perplexity = 50 , random-state = 0