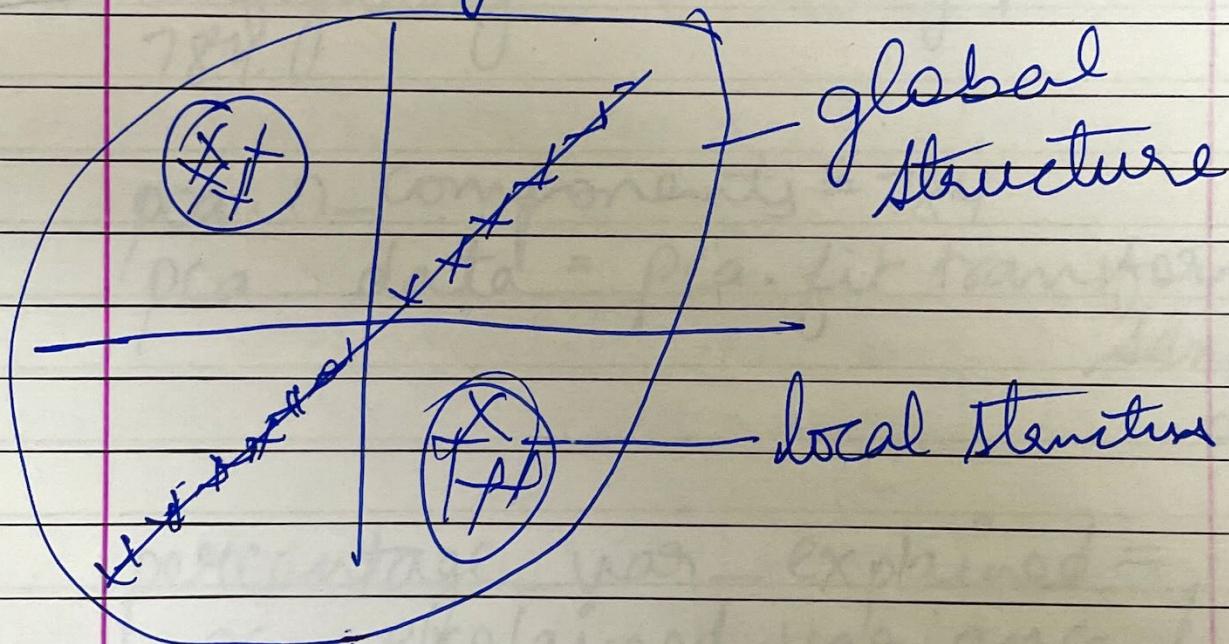


# t-SNE - t-distributed Neighbourhood Embedding

lec 1 PCA - Basic

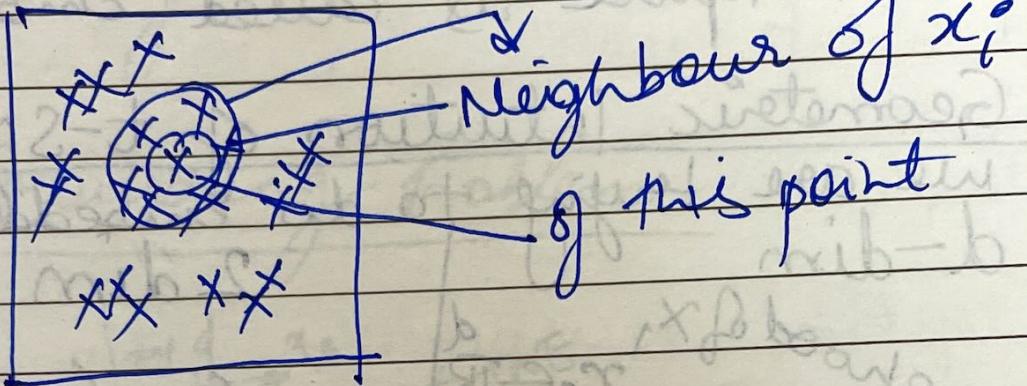
tSNE - Best dim reduction

PCA - tries to preserve the global shape of data.



t-SNE - preserves local structure

## lec2 Neighbourhood of a point, Embedding

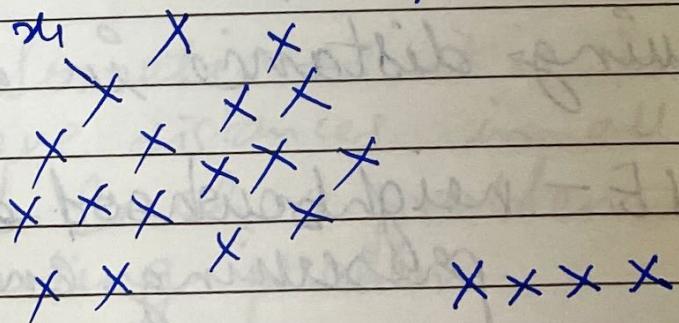


All points  $x_j$

$N(x_i) = \{x_j\}$ , s.t.  $x_i$  and  $x_j$  are geometrically close?

$$\|x_i - x_j\|^2 = \text{distance}^2$$

\*  $d$ -dimensional space:



2d.  $x^{a_1} x^{a_2}$

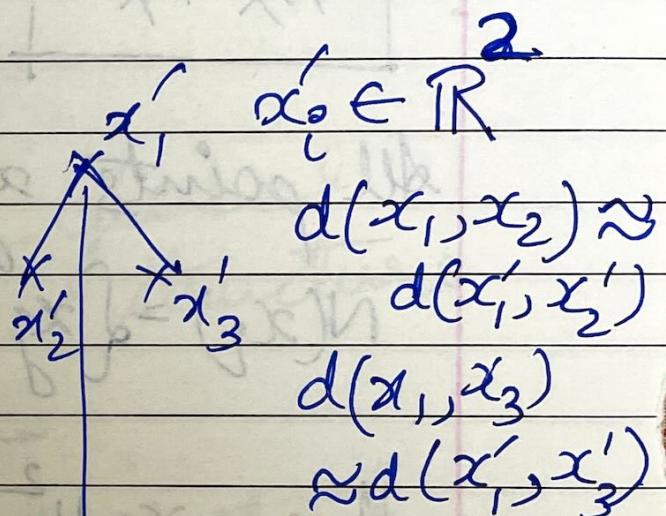
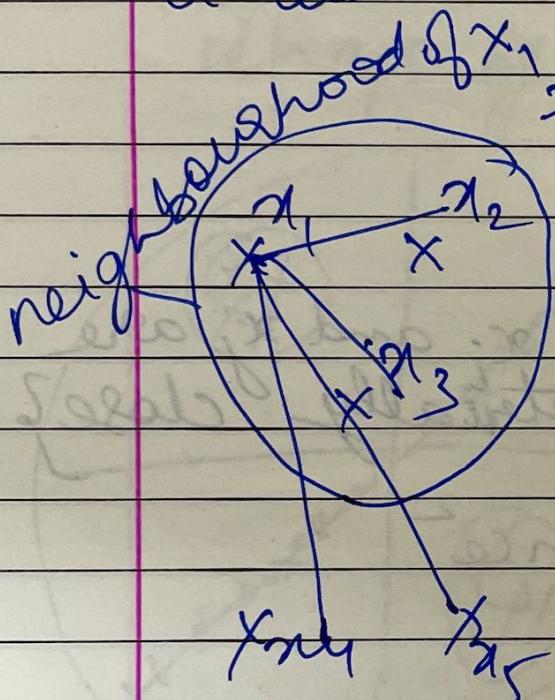
Every

~~Taking~~ points from high dim space, we have points in low-dim space is called Embedding

lec 3

### Geometric Intuition of t-SNE

We are trying to do embedding  
d-dim  $\rightarrow$  2 dim



+ need  
not  
be same.

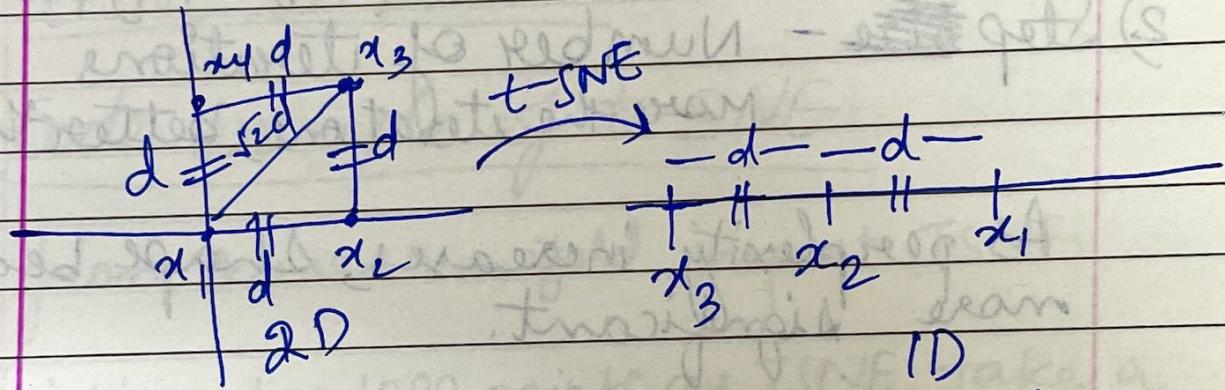
Preserving distance in neighbourhood.

t-SNE - neighbourhood ~~embedding~~  
preserving embedding

# Mathematical formulation

fairly advanced

## lec 4 Grounding Problem



Since  $x_3 \notin N_d(x_1)$  we don't have to preserve it.

But placing  $x_3$  makes distance b/w  $x_3$  &  $x_4$  as  $3d$  which is not preserved

So, sometimes it is impossible to preserve distances in all the neighbourhood. Such a problem is called Grounding problem.

## lec5 How to apply t-SNE and interpret its output

t-SNE works in iteration.

- 1) Perplexity - No. of ~~height~~ points in the neighbourhood which are getting preserved.
- 2) Step ~~size~~ - Number of iterations  
More the iterations, better the sol<sup>n</sup>

As perplexity increases, shape becomes more significant.

Always run t-SNE with multiple perplexity values.

If perplexity = Total datapoints you get a messy figure.

So perplexity < No. of datapoints

Always run iterations till the shape doesn't change much.

Stochastic means probabilistic

(\*) t-SNE expands dense clusters  
" shrinks sparse clusters

t-SNE does not preserve distance b/w clusters.

## lec6 t-SNE on MNIST

## lec7 Code example of t-SNE

from sklearn.manifold import TSNE

# picking top 1000 points as TSNE take a lot of time for 15K points

data\_1000 = standardized\_data[0:1000, :]

label\_1000 = labels[0:1000]

model = TSNE(n\_components=2,  
random\_state=0)



# Configuring the parameters

# the no. of points components = 2

# default perplexity = 30

# default learning rate = 2.00

# default Max. no. of iteration for the optimization = 1000

tsne\_data = model.fit\_transform(  
data\_1000)

# Creating a new data frame which helps us in plotting the result data

tsne\_data = np.vstack((tsne\_data,  
labels\_1000)).T

tsne\_df = pd.DataFrame(data=  
tsne\_data,  
columns=["Dim\_1", "Dim\_2",  
"label"])

## # Plotting the result of tsne

```
sns.FacetGrid(tsne_df, hue = "label",  
size=6).map(plt.scatter, "Dim1",  
"Dim2")  
plt.show()
```