

1. probability distribution

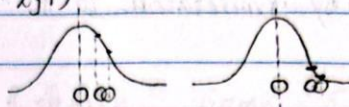
represents similarities between neighbors

$|x_i - x_j|$ Euclidean distance

↓ proportional to probability density
under a Gaussian centered at x_i

$$g(|x_i - x_j|)$$

You can distinguish
non-similar points
probability are



-sh between similar and
but absolute values of

much smaller

So, we fix that by dividing the current projection
value by the sum of the projections

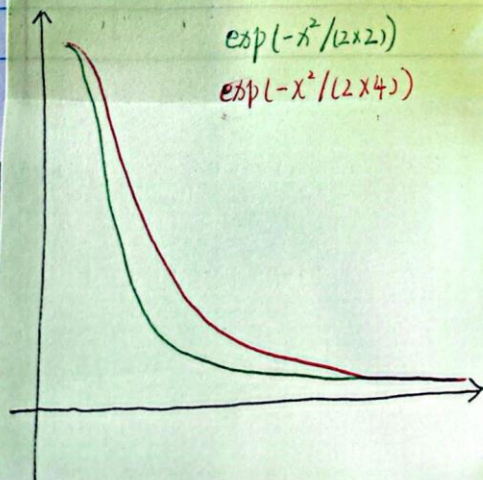
$$p_{j|i} = \frac{g(|x_i - x_j|)}{\sum_{k \neq i} g(|x_i - x_k|)}$$

$$p_{ij} = \frac{p_{j|i} + p_{i|j}}{2N}$$

N : number of data points.

$$p_{j|i} = \frac{\exp(-\|x_i - x_j\|^2 / 2\sigma_i^2)}{\sum_{k \neq i} \exp(-\|x_i - x_k\|^2 / 2\sigma_i^2)}$$

this is what exactly in t-SNE paper.



$$\exp(-x^2/(2 \times 2))$$

$$\exp(-x^2/(2 \times 4))$$

2. perplexity, sigma and target number of neighbors intuitive understanding:

A perplexity is more or less a target number of neighbors for our central point

Basically, \uparrow perplexity \rightarrow variance \uparrow

if we set perplexity to 4, it searches the right value of σ to "fit" 4 neighbors

Technical derivation.

"SNE performs a binary search for the value of σ that produces probability distribution with a fixed perplexity that is specified by the user

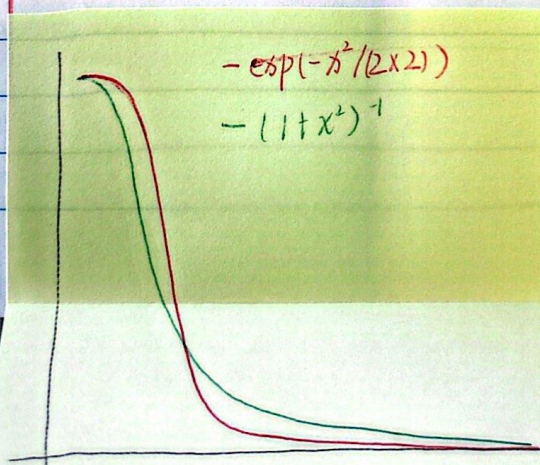
$$\text{Perp}(P_i) = 2^{-\sum_j P_{ji} \log_2 P_{ji}}$$

where $-\sum_j P_{ji} \log_2 P_{ji}$ is Shannon Entropy

Typical perplexity value ranges between 5 and 50

3. t-distribution & t-SNE.

for low-dimensional space, Gaussian creates crowding problem. To solve this, we are going to use student t-distribution with a single degree of freedom.



$$q_{ij} = \frac{(1 + \|y_i - y_j\|^2)^{-1}}{\sum_{k \neq l} (1 + \|y_k - y_l\|^2)^{-1}}$$

advantages of t :

1. It "falls" quickly and has a "long tail", so points won't get squashed into a single point.
2. we don't have to bother with σ^2 because we don't have one in q_{ij}

4. finding embedding in low dimensional space.

~~$$C = \sum_{x \in X} D_{KL}(P \| Q) = \sum_{x \in X} P(x) \log \left(\frac{P(x)}{Q(x)} \right)$$~~

$$C = KL(P \| Q) \quad \text{loss function}$$

$$= \sum_i \sum_j P_{ij} \log \frac{P_{ij}}{q_{ij}}$$

$$= \sum_i \sum_j (P_{ij} \log P_{ij} - P_{ij} \log q_{ij})$$

↓ Gradient descent

$$\frac{\partial C}{\partial y_i} = 4 \sum_j (P_{ij} - q_{ij}) (y_i - y_j) (1 + \|y_i - y_j\|^2)^{-1}$$

5. Tricks done in t-SNE to perform better.

early compression (not to focus on local groups)

early exaggeration.