where σ_i is the Gaussian variance centered on data point x_i. Given the redundancy of sensor data in high-dimensional space, we compress it to a lower dimension to enhance resource efficiency. The pair-wise affinity in this reduced space, q_{ij} (line 5), is computed as follow:

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

To minimize information loss during the above dimensionality reduction process, we minimize the Kullback-Leibler (KL) [27] divergence, a measure commonly used to assess the information loss between two probability distributions. Specifically, we minimize the KL divergence between p_{ij} and q_{ij}, which represent the high- and low-dimensional distributions of data point pairs, respectively. The optimization technique used in t-SNE is gradient descent, effectively minimizing the total KL divergence across data point pairs. The cost function C for this optimization is as follows:

$$C = KL(P||Q) = \sum_i \sum_j p_{ij} \log \frac{p_{ij}}{q_{ij}}. \tag{3}$$

where P is the affinity value in the high-dimensional space, Q is the corresponding affinity value in the low-dimensional space. The gradient formula is presented below:

$$\frac{\partial C}{\partial y_i} = 4 \sum_j (p_{ij} - q_{ij})(y_i - y_j). \tag{4}$$

Thus we have iteration as follows:

I AM AYMAAN SHAHZAD

$x^2+y^2=24$

$\dot{x}^{[i]}+y-1=45$

A2A group Team

Hello

$45+x-\acute{y}_i^{\Sigma}=\Sigma x^{[i]}$