Visualizing Data using t-SNE

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Data Visualization and Manifold Learning

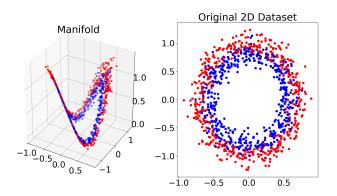
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Data Visualization and Manifold Learning

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- 2. We want to preserve as much structure between data points when mapping to a lower dimension.
- 3. What is the ideal case when reducing to 2D from a higher dimension?

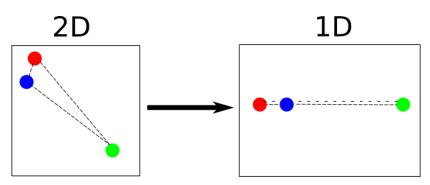
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Spring Metaphor

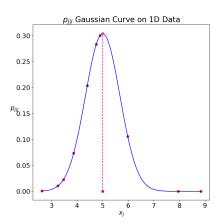
- Consider putting a spring between each point in higher-dimensional space, and then squashing the points down into a lower dimension.
- 2. Spring tension is given by neighbor locality.



What is $p_{j|i}$?

1.
$$p_{j|i} = \frac{\exp(-||x_i - x_j||^2/2\sigma_i^2)}{\sum_{k \neq i} \exp(-||x_i - x_k||^2/2\sigma_i^2)}$$

2. Probability datapoint x_i views x_j as its neighbor given Gaussian with variance σ_i



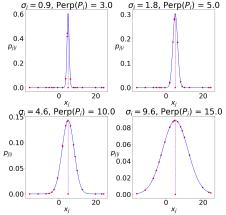
Determining σ_i

Perplexity Smooth approximation of number of neighbors $Perp(P_i) = 2^{H(P_i)}$

Shannon Entropy

Information present in probability space

$$H(P_i) = -\sum_j p_{j|i} \log_2 p_{j|i}$$



Gradient Descent Optimization

- 1. $q_{j|i}$ is analogous to $p_{j|i}$ for lower dimension points y_i and y_j . $\sigma = 1/\sqrt{2}$ for all $q_{i|i}$
- 2. Cost function is $C = \sum_{i} KL(P_i||Q_i) = \sum_{i} \sum_{j} p_{j|i} \log \frac{p_{j|i}}{q_{j|i}}$

3.
$$\frac{\partial C}{\partial y_i} = 2 \sum_j \left(p_{j|i} - q_{j|i} + p_{i|j} - q_{i|j} \right) \left(y_i - y_j \right)$$

4.
$$Y^{(t)} = Y^{(t-1)} + \nu \frac{\partial C}{\partial Y} + \alpha(t) \left(Y^{(t-1)} - Y^{(t-2)} \right)$$

5. Simulated annealing through decaying Gaussian noise

Problems with SNE

- ► Computational inefficiency
- Overcrowding