

Visualizing Data using t-SNE

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October 26, 2020

Data Visualization and Manifold Learning

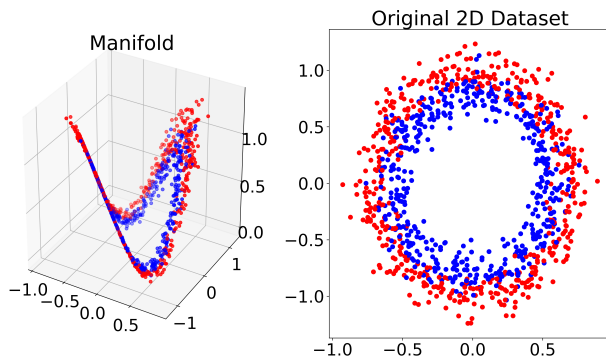
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Data Visualization and Manifold Learning

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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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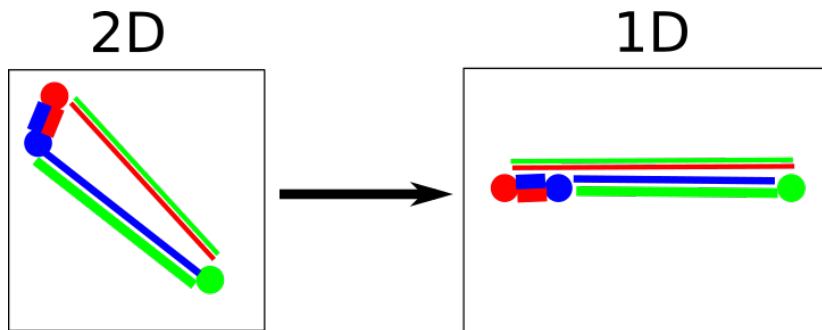
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Stochastic Neighbor Embedding (SNE)

High-Level Overview

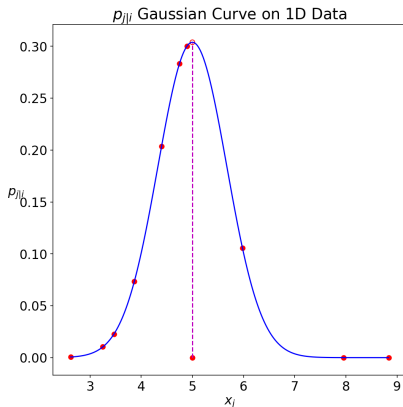
1. Each pair of data points has a measurable neighbor relationship with every other point
2. This relationship is non-symmetric
3. Stochastic neighbor embedding tries to preserve this relationship



Stochastic Neighbor Embedding (SNE)

What is $p_{j|i}$?

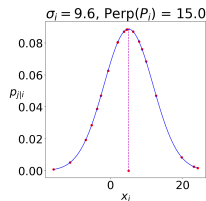
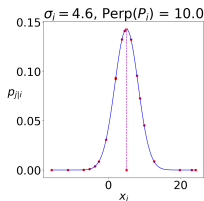
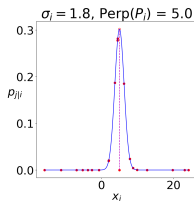
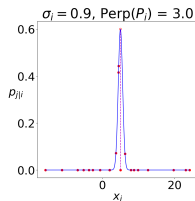
1. $p_{j|i} = \frac{\exp(-||x_i - x_j||^2 / 2\sigma_i^2)}{\sum_{k \neq i} \exp(-||x_i - x_k||^2 / 2\sigma_i^2)}$
2. Probability datapoint x_i views x_j as its neighbor given Gaussian with variance σ_i



Stochastic Neighbor Embedding (SNE)

Determining σ_i

σ_i	Determined via binary search on perplexity
Perplexity	Smooth approximation of number of neighbors $Perp(P_i) = 2^{H(P_i)}$
Shannon Entropy	Information present in probability space $H(P_i) = -\sum_j p_{j i} \log_2 p_{j i}$



Stochastic Neighbor Embedding (SNE)

Cost Function

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 $q_{j|i}$
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. Cost function uses Kullback-Leibler divergence to measure the difference between the set of $q_{j|i}$ and $p_{j|i}$

Stochastic Neighbor Embedding (SNE)

Gradient Descent Optimization

1. $\frac{\partial C}{\partial y_i} = 2 \sum_j \left(p_{j|i} - q_{j|i} + p_{i|j} - q_{i|j} \right) (y_i - y_j)$
2. $Y^{(t)} = Y^{(t-1)} + \nu \frac{\partial C}{\partial Y} + \alpha(t) \left(Y^{(t-1)} - Y^{(t-2)} \right)$
3. Simulated annealing through decaying Gaussian noise

Problems with SNE

- ▶ Cost function is not convex
 - ▶ Possible to get stuck on local minima
- ▶ Computational inefficiency
 - ▶ Must compute $p_{j|i}$ many times, especially when estimating σ_i
 - ▶ Simulated annealing is slow. Suffers compared to convex optimization
- ▶ Overcrowding