

A Brief Introduction to Dimensionality Reduction with t-SNE

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PCA – Dimensionality Reduction

- How it works
 - Projecting on to best hyper-plane
 - Minimize distances of far separated points
- Limitations
 - Linear algorithm, so it can't interpret complex non-linear relationships between features.
 - Focus on placing dissimilar data points far apart in a lower dimension representation.

t-SNE

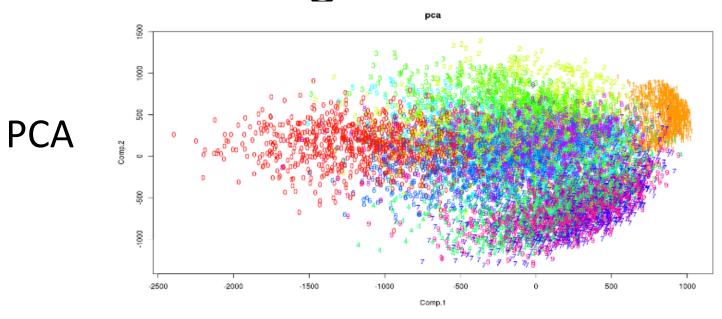
- t-Distributed Stochastic Neighbor Embedding
- Often it is important that similar data points be represented close together.
- t-SNE is based on probability distributions with gradient descent on neighborhood graphs to find the structure within the data.

Example: handwritten digits dataset

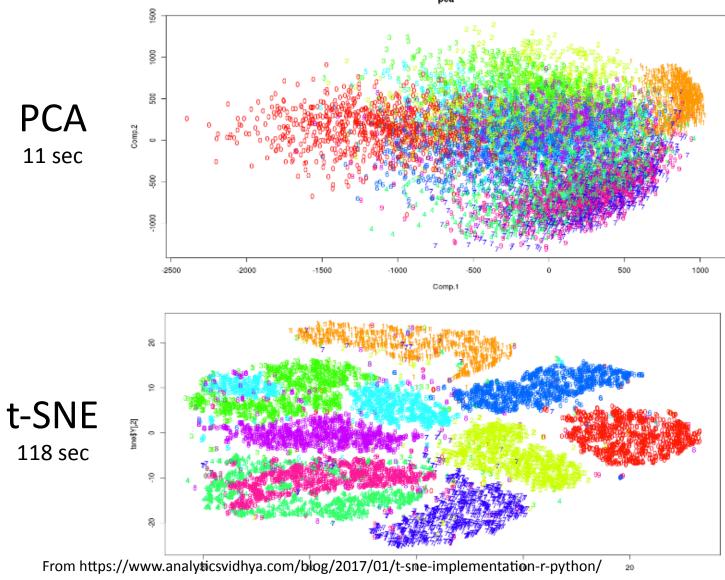




PCA Digits Visualization



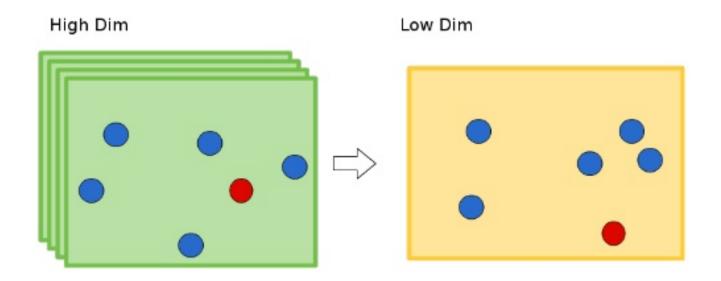
PCA vs t-SNE Digits Visualization



t-SNE Algorithm

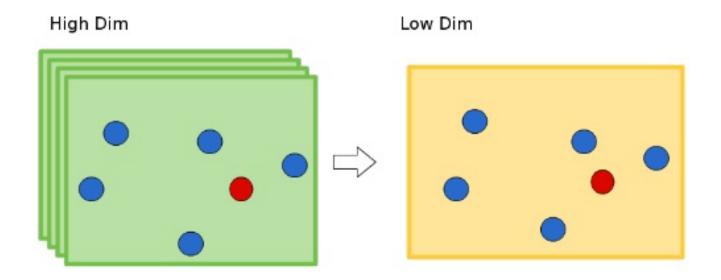
- Calculate the conditional probability of similarity between each pair of points in
 - High dimensional space
 - Low dimensional space
- Compute a cost function
 - Close neighbors should stay close
 - Middle and far neighbors may vary
 - "Normalized" by local density
- Gradient Descent

Map points – initially not so good



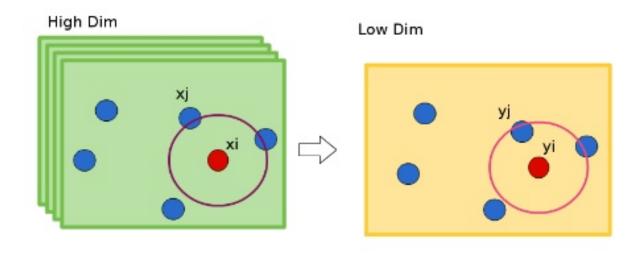
Map points - better

Preserve the neighborhood



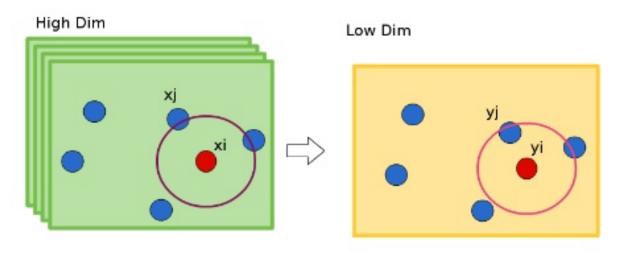
Measure Pairwise Similarities Create a Similarity Matrix

Measure pairwise similarities between high-dimensional and low-dimensonal objects



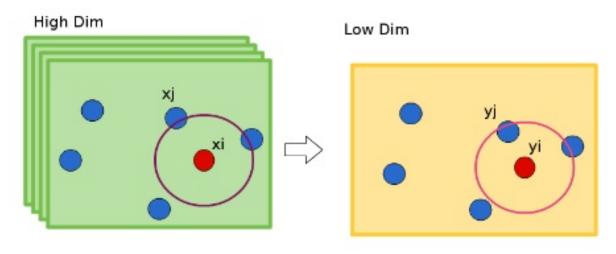
Create a Similarity Matrix Conditional Probabilities

Stochastic Neighbor Embedding (SNE) converts the high-dimensional Euclidean distances between data points into conditional probabilities that represent similarities (using t-Student distribution). Then do it for low-dim.



Create a Similarity Matrix Then make it better!

Stochastic Neighbor Embedding (SNE) converts the high-dimensional Euclidean distances between data points into conditional probabilities that represent similarities (using t-Student distribution). Then do it for low-dim.



SNE's cost function focuses on retaining the local structure of the data

Minimize the cost function by Gradient Descent

Demo

- How to Use t-SNE Effectively http://distill.pub/2016/misread-tsne/
 - 1a. Perplexity (5 to 50 is usually best)
 - 1b. Number of Iterations
 - 2. Cluster Size
 - t-SNE's measure of "distance" varies by local density
 - As a result, it naturally expands dense clusters, and contracts sparse ones, evening out cluster sizes.
 - 3. Cluster Distance
 - 5b. Shapes (2 bars)

Demo (continued)

- Square Grid
 - More points
 - Low perplexity
 - Very high perplexity
- Two Clusters, equal size
 - Very low perplexity => worms

References

- Laurens van der Maaten's t-SNE Github https://lvdmaaten.github.io/tsne/
- In depth presentation by Laurens van der Maaten https://www.youtube.com/watch? v=RJVL80Gg3IA&list=UUtXKDgv1AVoG88PLl8nGXmw#
- Analytics Vidhya blog <u>https://www.analyticsvidhya.com/blog/2017/01/t-sne-implementation-r-python/</u>
- https://en.wikipedia.org/wiki/Tdistributed_stochastic_neighbor_embedding
- http://scikit-learn.org/stable/modules/generated/ sklearn.manifold.TSNE.html
- https://www.slideshare.net/ssuserb667a8/visualization-datausing-tsne

Thank You!

