

Methods and Algorithms

Spring 2026

1 Problem

2 Method

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4 Practice

5 Decision Framework

**By the end of this lecture, you will be able to:**

- ➊ Apply PCA for dimensionality reduction and feature extraction
- ➋ Interpret variance explained and choose number of components
- ➌ Use t-SNE for visualization of high-dimensional data
- ➍ Compare linear (PCA) vs non-linear (t-SNE) methods

**Finance Application:** Portfolio risk decomposition, asset clustering

*From many features to meaningful low-dimensional representations*

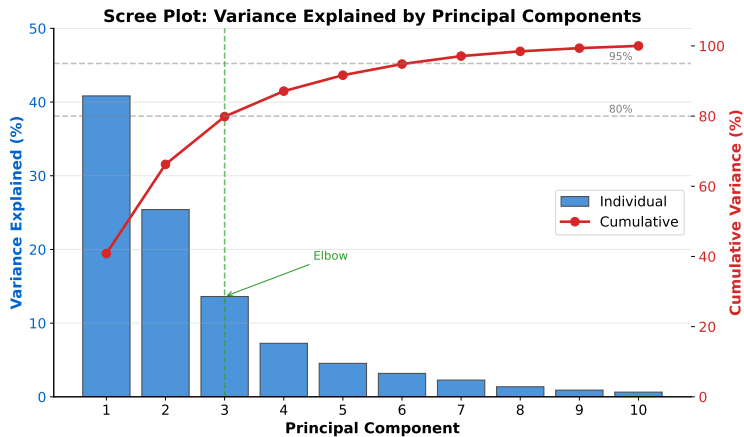
## Curse of Dimensionality

- Portfolio with 100+ assets: hard to visualize relationships
- Customer data with dozens of features: redundant information
- High dimensions cause sparsity and computational issues

## Solutions

- **PCA**: Linear projection preserving maximum variance
- **t-SNE**: Non-linear embedding preserving local structure

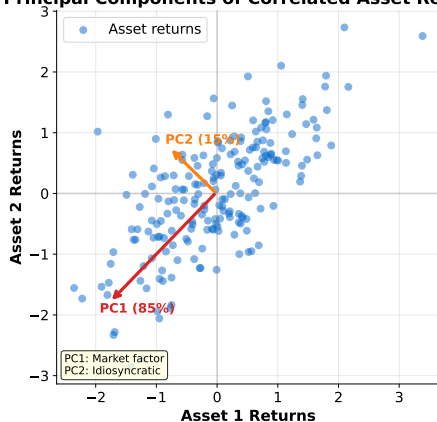
*Reduce dimensions while preserving important information*



[https://github.com/Digital-AI-Finance/methods-algorithms/tree/master/slides/L05\\_PCA\\_tSNE/01\\_scree\\_plot](https://github.com/Digital-AI-Finance/methods-algorithms/tree/master/slides/L05_PCA_tSNE/01_scree_plot)

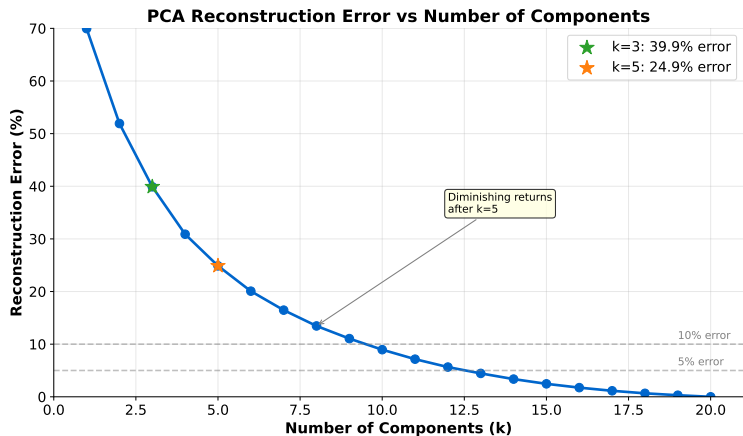
*Choose  $k$  components capturing 80-95% of variance, or at the “elbow”*

## Principal Components of Correlated Asset Returns



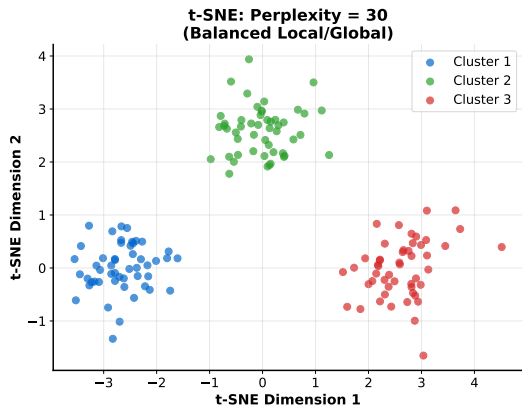
[https://github.com/Digital-AI-Finance/methods-algorithms/tree/master/slides/L05\\_PCA\\_tSNE/02\\_principal\\_components](https://github.com/Digital-AI-Finance/methods-algorithms/tree/master/slides/L05_PCA_tSNE/02_principal_components)

*Principal components are orthogonal directions of maximum variance*



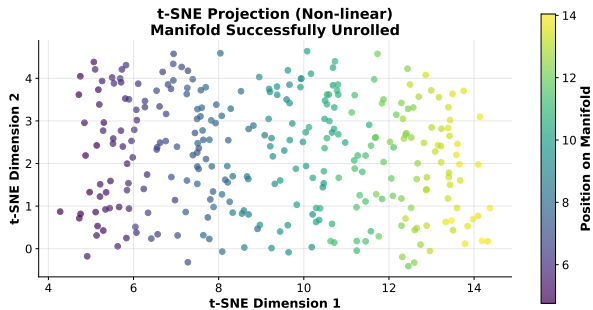
[https://github.com/Digital-AI-Finance/methods-algorithms/tree/master/slides/L05\\_PCA\\_tSNE/03\\_reconstruction](https://github.com/Digital-AI-Finance/methods-algorithms/tree/master/slides/L05_PCA_tSNE/03_reconstruction)

*More components = lower error, but diminishing returns after elbow*



*Perplexity controls local vs global structure preservation (try 5-50)*

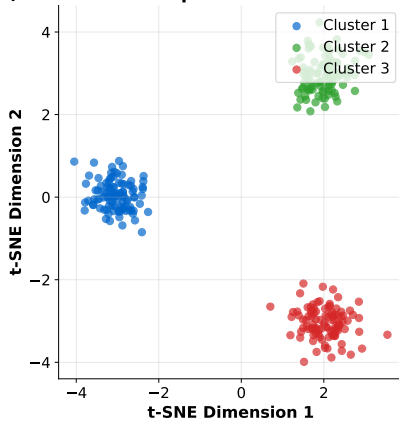




[https://github.com/Digital-AI-Finance/methods-algorithms/tree/master/slides/L05\\_PCA\\_tSNE/05b\\_tsne\\_swiss\\_roll](https://github.com/Digital-AI-Finance/methods-algorithms/tree/master/slides/L05_PCA_tSNE/05b_tsne_swiss_roll)

*t-SNE unrolls non-linear manifolds that PCA cannot handle*

### t-SNE Projection (Clear Cluster Separation - Local Structure)



[https://github.com/Digital-AI-Finance/methods-algorithms/tree/master/slides/L05\\_PCA\\_tSNE/06c\\_tsne\\_cluster\\_projection](https://github.com/Digital-AI-Finance/methods-algorithms/tree/master/slides/L05_PCA_tSNE/06c_tsne_cluster_projection)

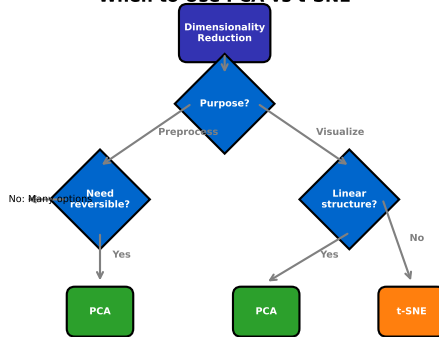
*t-SNE better preserves cluster structure for visualization*

## Open the Colab Notebook

- Exercise 1: Apply PCA to high-dimensional finance data
- Exercise 2: Visualize clusters with t-SNE
- Exercise 3: Compare PCA vs t-SNE for different datasets

**Link:** <https://colab.research.google.com/> [TBD]

## When to Use PCA vs t-SNE



*PCA: Fast, linear, reversible, for preprocessing*

*t-SNE: Slow, non-linear, visualization only, preserves local structure*

[https://github.com/Digital-AI-Finance/methods-algorithms/tree/master/slides/L05\\_PCA\\_tSNE/07\\_decision\\_flowchart](https://github.com/Digital-AI-Finance/methods-algorithms/tree/master/slides/L05_PCA_tSNE/07_decision_flowchart)

*PCA for preprocessing/speed, t-SNE for visualization only*

- Jolliffe, I.T. (2002). *Principal Component Analysis*. Springer.
- van der Maaten, L. & Hinton, G. (2008). *Visualizing Data using t-SNE*. JMLR.
- James et al. (2021). *Introduction to Statistical Learning*. <https://www.statlearning.com/>