

# L05: PCA & t-SNE

Dimensionality Reduction for Visualization and Preprocessing

Methods and Algorithms

Spring 2026

- 1 Problem
- 2 Method
- 3 Solution
- 4 Practice
- 5 Decision Framework
- 6 Summary

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

1. Apply PCA for dimensionality reduction and feature extraction
2. Interpret variance explained and choose number of components
3. Use t-SNE for visualization of high-dimensional data
4. 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

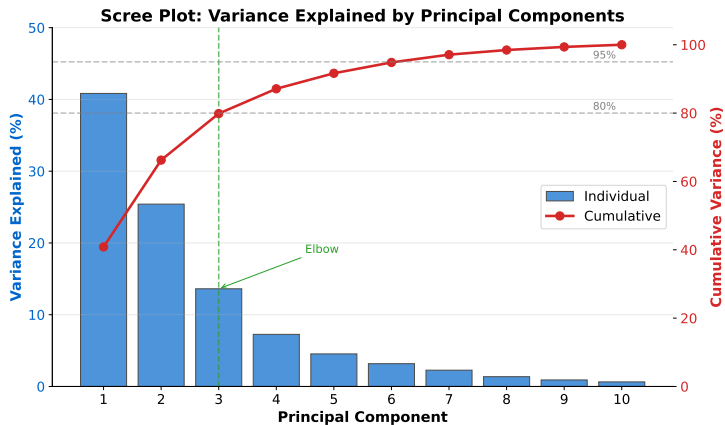
## Solutions

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

---

Reduce dimensions while preserving important information

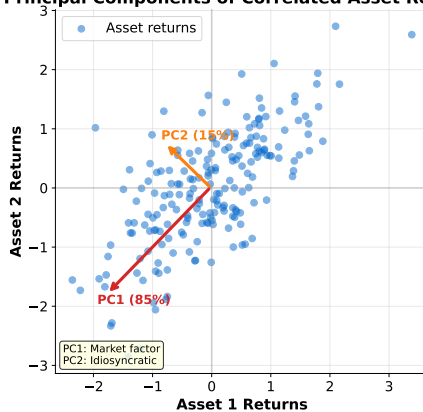
# Scree Plot: Choosing Components



[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)

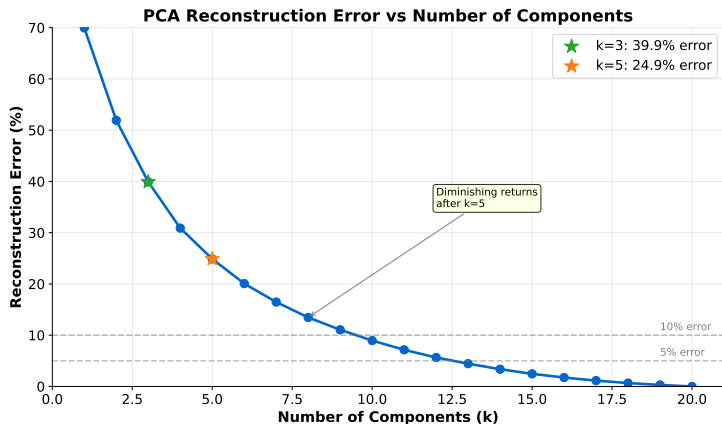
Choose  $k$  components capturing 80-95% of variance, or at the “elbow”

## 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)

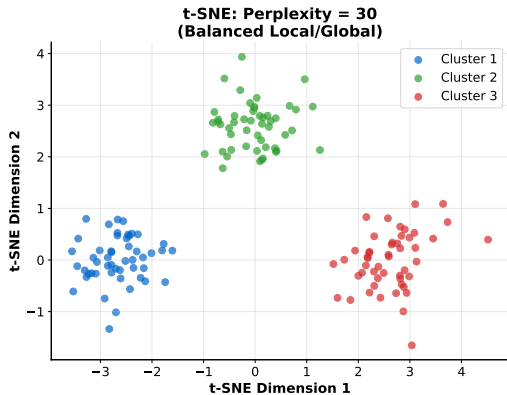
Principal components are orthogonal directions of maximum variance



[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)

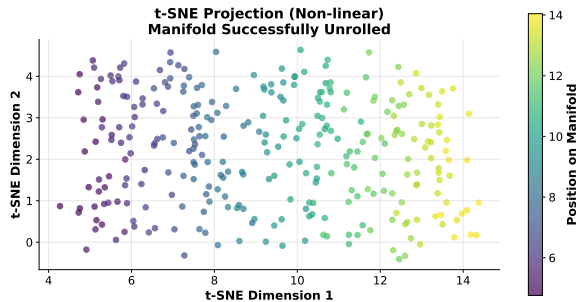
More components = lower error, but diminishing returns after elbow

## t-SNE: Perplexity Effect



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

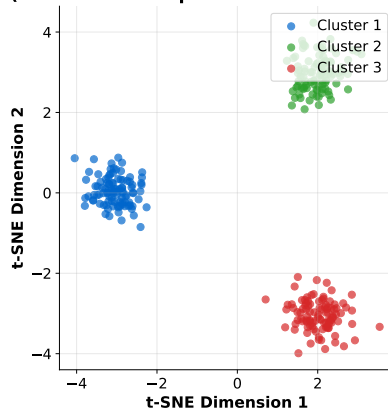




[https://github.com/Digital-AI-Finance/methods-algorithms/tree/master/slides/L05\\_PCA\\_tSNE/05b\\_tSNE/swiss\\_roll](https://github.com/Digital-AI-Finance/methods-algorithms/tree/master/slides/L05_PCA_tSNE/05b_tSNE/swiss_roll)

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

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



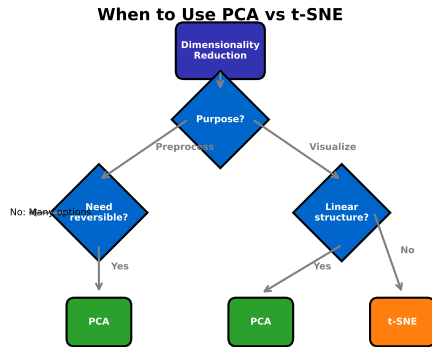
[https://github.com/Digital-AI-Finance/methods-algorithms/tree/master/slides/L05\\_PCA\\_tsNE/06c\\_tsne\\_cluster\\_projection](https://github.com/Digital-AI-Finance/methods-algorithms/tree/master/slides/L05_PCA_tsNE/06c_tsne_cluster_projection)

**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]



*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/>