Practitioner Brief

AI IN ASSET MANAGEMENT

Unsupervised Learning II: Network Theory

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Network theory has long been part of mathematics, the sciences, and data analysis. What is new, which this chapter of *AI in Asset Management: Tools, Applications, and Frontiers* highlights, is how these methods can be applied to practical investment problems.

Alongside classical tools, such as clustering and centrality, newer machine learning (ML) approaches, such as graph neural networks (GNNs)—models that learn from both fundamentals and the relationships between assets—make it possible to map connections dynamically, uncover hidden asset clusters, and forecast contagion with greater speed and precision.

For practitioners, the value is immediate: smarter diversification, stronger risk management, and earlier warning signals of market stress. This Practitioner Brief translates those advances into tools portfolio managers, risk managers, traders, and quants can put to work.

Who Should Read This Chapter?

This chapter is written for the front line of investment professionals—portfolio managers, risk managers, quants, and traders—equipping them with practical tools in four areas: diversification, systemic risk detection, forecasting, and predictive modeling. While these models serve immediate decision making on the ground, their insights also extend across the organization, informing strategy at the top and risk allocation throughout the enterprise.

"The intricate reality of interconnectedness is not captured by the conventional perspective of isolated actors or homogeneous systems. Network theory provides a strong framework for explicitly modeling these connections."

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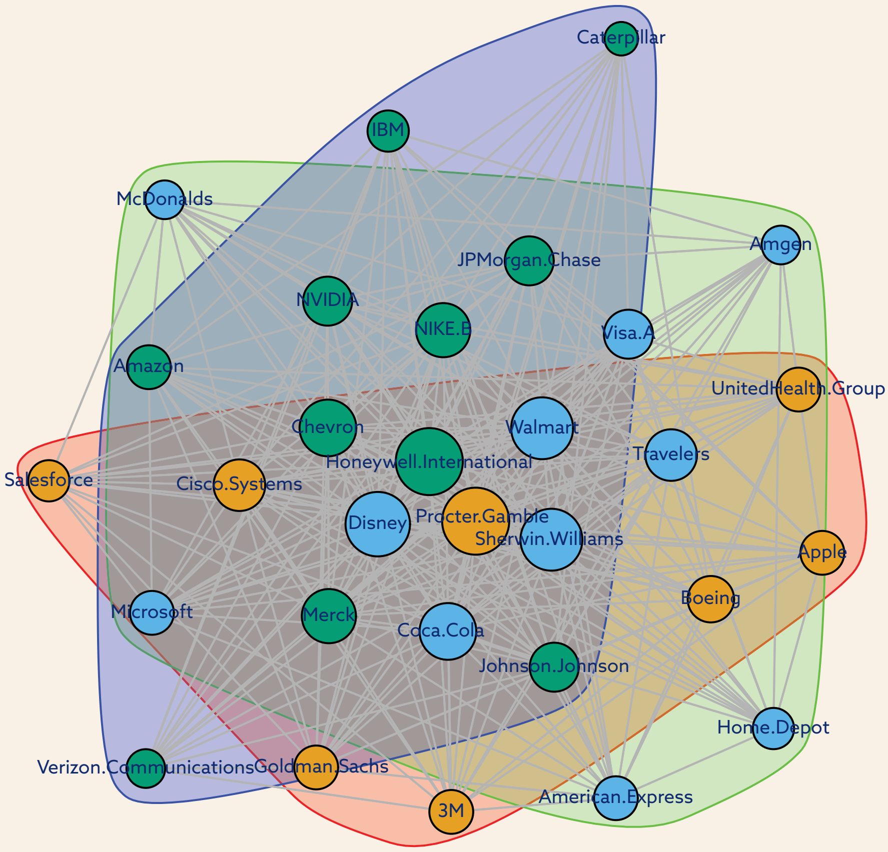
Practical Applications

Diversification and portfolio construction

- *Concept:* Hidden clusters exist beyond sectors; true diversification spreads across them.
- *Methods:* Methods include clustering algorithms (Louvain, Spinglass, hierarchical, *k*-means); minimum spanning trees (MSTs); centrality-based weighting; and network risk parity.
- *Who benefits:* Portfolio managers and chief investment officers (CIOs) benefit. For example, COVID-19 showed travel, energy, and hospitality stocks behaving as one cluster despite sector labels.

A Correlation-Based Network for the Dow Jones Industrial Average Index



Note: Example of community detection—hidden clusters that aren't visible from sector labels. This figure illustrates the Dow Jones Industrial Average Index with a correlation-based network and the Cluster Spinglass algorithm according to the highest modularity score.

Source: Bloomberg, LLC. This exhibit appeared as Exhibit 5 in G. S. Konstantinov and A. Sadeghi, "Unsupervised Learning II: Network Theory," in *AI in Asset Management: Tools, Applications, and Frontiers* (2025).

Systemic risk and contagion

- *Concept:* Nodes that are hubs and links that serve as bridges amplify shocks; their failure spreads risk.
- *Methods:* Methods include centrality measures (degree, eigenvector, betweenness, closeness); contagion modeling (direct and indirect linkages); metrics density; reciprocity; and clustering.
- *Who benefits:* Risk managers and chief risk officers (CROs) benefit—for example, Lehman Brothers' collapse as a hub failure and AIG's near default as counterparty contagion.

Market forecasting and signals

- *Concept:* Shifts in network structure can flag regime changes before they appear in prices.
- *Methods:* Methods include real-time monitoring of connectivity metrics combined with AI models. Networks can learn which links matter most, weighting relationships dynamically to detect instability.
- *Who benefits:* Traders and strategists benefit through early warning of volatility spikes, breakdowns in diversification, and market regime shifts.

Predictive modeling and AI

- *Concept:* Networks capture spillovers and dependencies that shape asset prices, transactions, and markets.
- *Methods:* Methods include GNNs, graph attention networks (GATs), and network features (entropy, modularity, fragility, Ricci curvature) in ML/DL (deep learning) models.
- *Who benefits:* Quant researchers and data scientists benefit through the enhancement of forecasting by combining fundamentals with network structure.

Example of community detection—hidden clusters that aren't visible from sector labels. Using Dow Jones Industrial Average Index with correlation-based network and the Cluster Spinglass algorithm according to the highest modularity score.

Practitioner Toolkit

Objective	Tool/Technique	Who Uses It	How It's Applied in Practice	What It Delivers
Build and visualize financial networks	Python (NetworkX), R/igraph, Gephi	Quant researchers, data scientists	Construct and visualize networks of assets, institutions, or exposures using correlations, transactions, or flows. Identify hubs, bridges, and clusters visually	Intuitive maps of market structure; faster detection of connected exposures
Detect hidden clusters for diversification	Louvain, SpinGlass, hierarchical, k-means clustering	Portfolio managers, CIOs	Reveal relationships beyond sectors or geographies to find true diversification opportunities	Improved portfolio diversification and early warnings of concentration risk
Simplify network complexity	Minimum spanning tree (MST), filtering algorithms	Risk managers, CROs	Reduce dense correlation matrices to essential structures, keeping only the strongest connections	Clearer risk visualization highlighting systemic nodes and contagion paths
Measure systemic importance	Centrality metrics (degree, eigenvector, betweenness, closeness)	Risk and portfolio analysts	Quantify each node's influence and highlight those whose failure could amplify contagion or signal fragility	Prioritized monitoring of systemically important assets or institutions
Forecast and monitor market signals	Connectivity metrics (density, modularity, reciprocity) + ML models	Traders, strategists	Track structural changes in network topology that often precede volatility or regime shifts	Early insight into market instability and breakdowns in diversification
Model networked relationships with AI	Graph neural networks (GNNs), graph attention networks (GATs)	Quant researchers, strategists	Combine fundamentals with relational data to model dependencies and forecast spillover effects	Dynamic, data-driven forecasts with higher predict

Workflow

This high-level workflow summarizes how AI strengthens each stage of network analysis.

Define: Select the type of financial network (assets, factors, interbank lending, derivatives, supply chains).

Map: Represent nodes (institutions, assets, countries, geographies) and edges (correlations, money transfers, goods, services, packages, loans, exposures), enriched with fundamentals, flows, or sentiment.

Analyze: Apply appropriate clustering, filtering, centrality, or AI methods.

Draw insights: Improve diversification, identify hubs and bridges, and run contagion simulations, which are now possible dynamically and at scale with AI.

The Bottom Line

Network analysis has been part of data science for years; what is new is its application to real investment problems, supported by modern machine learning tools. By mapping hidden clusters, tracing contagion pathways, and monitoring signals dynamically and at scale, investment professionals gain earlier insight, stronger diversification, and more resilient risk management. For portfolio managers, risk officers, traders, and quants, the message is clear: Network theory, powered by AI, is ready for the front line of finance.

Metrics That Matter

From the many measures available, the chapter highlights three metrics as especially critical for practitioners: density, modularity, and degree centrality.

- *Connectivity metrics—density:* This is the ratio of actual to possible connections in a network (0–1). Higher density means stronger connectivity; above ≈0.6, diversification is limited and fragility increases. However, real networks are sparse, with density below 0.2.
- *Community metrics—modularity:* This measures the strength of community structure. Values greater than 0.3 typically indicate strong clusters, useful for detecting hidden asset groups (see Practical Applications, "Diversification and portfolio construction").
- *Systemic importance metrics—degree centrality:* This measures the average connectedness of each individual node in the network, irrespective of their connections to other nodes. In essence, it quantifies the number of edges connected to a node.

Glossary

Bridge: A node that links communities; its distress can transmit shocks across groups.

Centrality: A family of measures that assess a node's importance (e.g., degree, eigenvector, closeness, betweenness).

Cluster (community): A group of nodes more tightly linked to each other than to the rest of the network.

Contagion: The spread of shocks or stress through a network via direct or indirect linkages.

Edge: The connection between nodes—for example, correlations, loans, counterparty exposures, ownership links.

Hub: A highly connected node whose failure can destabilize the system.

Minimum spanning tree: A simplified version of a network that retains only the strongest links, helping highlight key structures.

Node: An entity in the network—for example, a stock, bank, fund, firm, or country.

Related Content

Cao, Larry, ed. 2023. *Handbook of Artificial Intelligence and Big Data Applications in Investments*. CFA Institute Research Foundation. https://rpc.cfainstitute.org/research/foundation/2023/ai-and-big-data-in-investments-handbook.

CFA Institute Research and Policy Center. 2025. "The Automation Ahead: Exploring the Next Frontier of Investment Automation." https://rpc.cfainstitute.org/research/the-automation-ahead-content-series.

Fabozzi, Frank J., Andrew Chin, Igor Yelnik, and Jim Kyung-Soo Liew. 2025. "The Disappearing Edge: AI, Machine Learning, and the Future of the Discretionary Portfolio Manager." *Financial Analysts Journal* 81 (4). https://rpc.cfainstitute.org/research/financial-analysts-journal/2025/disappearing-edge-ai-machine-learning.

Wilson, Cheryll-Ann. 2025. "Creating Value from Big Data in the Investment Management Process: A Workflow Analysis." CFA Institute Research and Policy Center. https://rpc.cfainstitute.org/research/reports/2025/creating-value-from-big-data-in-the-investment-management-process.

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