# Chapter 16
# Networks and AI: Outline

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## 16.1 Introduction

- Why networks matter in economics and econometrics (social interactions, information, trade/production, finance, systemic risk, etc).
- Distinguishing network econometrics from spatial econometrics (link to Ch. 7).
- Roadmap: evolution from spatial models → social interactions → network econometrics → AI/ML on graphs; from fixed networks, to strategic link formation, to learned representations (embeddings/GNNs).
- Scope and objectives of the chapter.

### Part I: Foundations

*We start from early matrix-based spatial tools and show how network economists generalised them to observed social/economic networks, and then extended to formation and causal designs under spillovers.*

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## 16.2 Spatial Models and Social Interactions (1970s–1990s)

**Topics:**

- SAR/SEM, spatial weights matrices, distance-based dependence and applications.
- Manski (1993): reflection problem, linear-in-means social interaction models.
- Early quasi-network applications.

**Lessons:**

- Aged well: introduction of the weights-matrix framework, later generalized to networks.
- Aged not-so well: over-reliance on makeshift "neighbour" definitions (often unvalidated proxies for economic/social interaction), often treating geography as the main channel instead of the social/economic links.
- Results were often fragile; Manski's reflection problem put identification considerations at the core of future model developments, which ultimately shaped modern network econometrics.

## 16.3 The Emergence of Network Econometrics (1990s–2000s)

**Topics:**

- What economists mean by "networks": nodes, links, adjacency matrices; undirected vs directed, weighted vs unweighted; contrast with spatial weights.
- Peer-effects models on observed networks.
- IV/GMM/QMLE for network autoregression.
- First systematic use of real network data (school friendship networks, firm and interbank linkages, trade networks).

**Lessons:**

- Aged well: attaching explicit network structure improved interpretability (who affects whom and through which connections) and helped with identification clarity; extending spatial tools to arbitrary graphs expanded the applications of workhorse models.
- Aged not-so well: early models treated networks as fixed; links in many economics problems are often endogenous and mismeasured.
- Assuming the observed network as given in regressions was a natural first step; however, selection/formation issues became central to modeling after the initial stages.

## 16.4 Modelling Network Formation

**Topics:**

- Descriptive network metrics as econometric inputs (degree, centrality, clustering).
- Statistical models of network formation: dyadic regression, ERGMs, homophily and triadic closure.
- Tension in 2000s/2010s: move toward micro-founded / tractable statistical formation models.
- Game-theoretic and strategic models of network formation; equilibrium concepts and identification.
- Estimation techniques: pseudo-likelihood, method of moments, simulation-based estimation; computational challenges.

**Lessons:**

- Aged well: strategic models of network formation; modelling that explains why links form (preferences, economic constraints, policy interventions).
- Aged not-so well: highly parametrized ERGMs get computationally fragile and hard to diagnose.
- Micro-founded and interpretable formation models are a crucial part of modern networks econometrics development; link endogeneity matters for inference.

## 16.5 Interference, Experiments, and Causal Effects

**Topics:**

- Interference and violations of SUTVA on networks.
- Experimental and quasi-experimental designs on networks: cluster randomisation, saturation designs, graph partitioning.
- Exposure mappings, direct and spillover effects.
- Randomisation inference and variance under network dependence.

**Lessons:**

- Aged well: design-based approaches (explicit treatment assignment and exposure definitions).
- Aged not-so well: old practice of implicit assumptions of no interference on networks; spillovers are central to the estimation.
- Direct vs spillover effects delineation and careful design structuring become central under network dependence.

**Part II: Big-Data and AI Era**

*We next turn to the big-data shift: as networks become larger and more richly measured, high-dimensionality issues and computational constraints come to the forefront; ML methods enter the toolkits for network studies.*

## 16.6 Network Econometrics in the Big-Data Era

**Topics:**

- New data sources: administrative registers, online platforms, financial networks.
- High dimensional networks (many nodes, many attributes) and the curse of dimensionality; sparsity methods.
- Embeddings and node representations for econometrics.
- Evolving networks, state-dependent links.
- Network dependence at scale: sparse vs dense graphs shape what "large-n" means; naïve i.i.d. inference and off-the-shelf clustering can fail, motivating graph-robust inference, scalable estimators, and dependence-aware validation.

**Lessons:**

- Aged well: regularization/scalable estimation; many classical approaches become unfeasible at the modern data scale; dynamic methods.
- Aged not-so well: naïve use and interpretation of embeddings.
- Rich new network data expanded the set of feasible economics problems, but moved constraints to significant computational issues; successful approaches combine scalable algorithms with economic transparency.

## 16.7 AI & Machine Learning for Network Data

**Topics:**

- Probabilistic Graphical Models and Network Dependence.
    - Economic applications: credit risk, contagion, macro-financial linkages.
- Deep Learning and Graph Neural Networks.
    - Representation learning on graphs; message-passing neural networks and GNNs.
    - Conceptual bridge: GNNs as a nonlinear successor to SAR/spatial lag models.
    - Economic applications: link prediction, recommendation systems and matching platforms, fraud detection.
- Causal Machine Learning under Network Interference: adapting causal ML to settings with interference and spillovers.
- LLM-constructed Economic Networks.
    - Text-based economic networks: supply chains, citation and knowledge graphs.
    - Accompanying issues: measurement error, bias and validation problems.

**Lessons:**

- Aged well: scalable algorithms, computational advances; graph-based ML used for scalable approximation of network-structured dependence and for capturing nonlinearities that traditional linear spillover models miss.
- Aged not-so well: black-box predictions, limited interpretability, lack of economic microfoundation; good-fit models do not imply causal or policy-relevant conclusions; pitfalls include edge-based train/test leakage and non-stationarity as platforms or network rules evolve.
- Validation issues are a bottleneck; credibility of AI on networks requires careful sensitivity analysis to network measurement/formation and ideally is formed around economic structure.

**Part III: Economics & Interpretation**

*We close by showing how methodological developments affect the economics-of-networks research areas; what we can learn about welfare, diffusion, and systemic risk once econometrics handles formation and spillovers.*

## 16.8 Connections to the Economics of Networks

**Topics:**

- Econometrics of Networks and AI applications to key economics-of-networks themes:
  - Welfare and efficiency of network structures;
  - Inequality;
  - Diffusion of information, technology, norms;
  - Contagion issues and systemic risk in financial and production networks.
- Case studies (social networks / firm supply chains / financial networks).
- Policy hook: optimal intervention/targeting on networks, illustrating where econometrics + AI can change decisions rather than only improve prediction.

## 16.9 General Lessons

- Aged well: clear identification, linear-in-means, strategic formation, network experiments.
- At risk: complex ERGMs without diagnostics, uninterpretable black-box ML.
- Principles of surviving relevance: clarity + causal structure + scalability, plus measurement/validation as a first-class object.

## 16.10 Looking Ahead

- Privacy-preserving networks, dynamic networks, high-frequency data.
- Hybrid methods bridging econometrics $\leftrightarrow$ GNNs $\leftrightarrow$ generative models.
- Outlook for next decade.

## 16.11 Conclusions