

# Spatial approximation of sparsely sampled networks

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# Motivation

# Motivation

- ▶ Interaction among firms is important for performance.
  - ▶ Spatial economics: trade costs, Marshallian externalities.
  - ▶ Urban economics evidence: firms in dense areas are more productive.
  - ▶ Network methods: input-output linkages matter.
- ▶ How to measure the strength of interaction and its effect on performance?
- ▶ Quantifiable spatial economics models: geography of space matters, but we can quantify its impact.

# Buyer-seller networks

- ▶  $N$  buyers and  $K$  sellers.
- ▶ How do buyer-seller links correlate with firm performance? (No causal analysis so far.)
- ▶ Conceptual/computational problems:
  - ▶ there are  $N \times K$  potential buyer-seller links.
  - ▶ links may vary over time.

## Model

## A balls-and-bins model of link reporting

- ▶ How much did firm  $n$  buy from firm  $k$  last month (week, day, hour, minute, second)?

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- ▶ How much did firm  $n$  buy from firm  $k$  last month (week, day, hour, minute, second)?
- ▶ As Armenter and Koren (2013) show, not much can be solved by time aggregation.
- ▶ Instead, model

$$\Pr(G_{nk} = 1).$$

## Poisson process for link reporting

$$\Pr(G_{nk,t,t+h} = 1) = 1 - e^{-\lambda_{nk}h} \approx \lambda_{nk}h$$



# Dimension reduction

- ▶ Both statistical learning and theorizing are about *dimension reduction*: map complex problem into fewer dimensions.
- ▶ Can we make this explicit for the buyer-seller problem?

## A spatial model

- ▶ Buyer  $n$  is located at  $X_n \in \mathbb{R}^M$ . ( $1 < M \ll K$ )
- ▶ Seller  $k$  is located at  $Y_k \in \mathbb{R}^M$ . ( $1 < M \ll N$ )

## Buyer-seller links

- Probability of a link depends on (squared) Euclidean distance

$$-\sum_{m=1}^M (x_{nm} - y_{km})^2 = -\sum_{m=1}^M x_{nm}^2 - \sum_{m=1}^M y_{km}^2 + \sum_{m=1}^M x_{nm} y_{km} = \mu_n + \nu_k + \sum_{m=1}^M x_{nm} y_{km}$$

# Matrix factorization

- ▶ But the last term is exactly as in matrix factorization models. (Recommendation engines, Netflix prize)

$$\Pr(G_{nk} = 1 | X_n, Y_k) = \mu_n + \nu_k + X_n Y_k$$

$$\mathbf{G} \approx \mu + \nu + \mathbf{XY}$$

- ▶ This approximates  $G$  with a low-rank matrix (e.g., singular value decomposition).
- ▶ When  $M = 1$ ,  $X, Y \approx$  Pagerank, worker-firm fixed effects.

## Firm performance

- ▶ Node-level performance,

$$Q_n = f(X_n).$$

- ▶ This encompasses spatial amenities (good  $X$ ) and agglomeration (good neighbors).

# Questions

## Answerable

- ▶ How does firm position in network account for inequality in firm performance?

$$dQ_n \approx \sum f_m dX_{nm}$$

- ▶ What are  $X_n$ s correlated with?

## Not yet

- ▶ How much of it is amenities vs agglomeration? ( $X$  vs  $G$ )
- ▶ What if firms choose  $X_n$  endogenously?
- ▶ Do returns to  $X_n$  change in equilibrium? (optimal transport?)

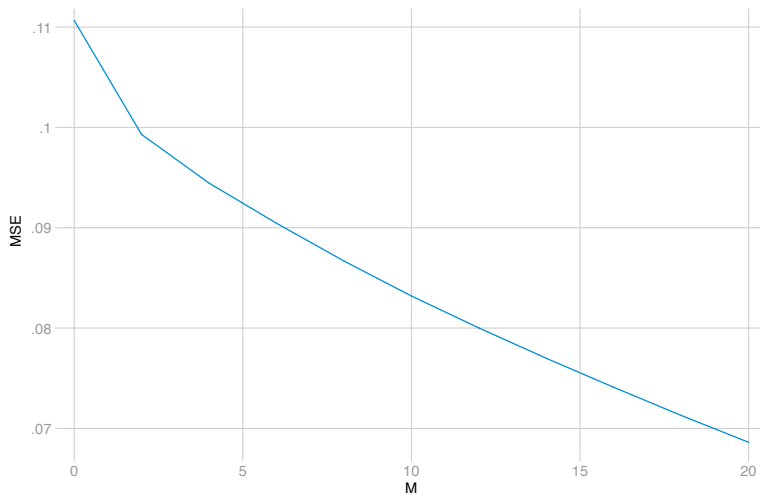
# Applications

# Procurement network

- ▶ Buyers,  $N = 8300$ .
- ▶ Sellers,  $K = 27400$ .
- ▶ Edges: 86900.
- ▶ Work with  $100 \times 500$  matrix for now.
- ▶ Train: 2010..2014, test: 2015..2017



## Goodness of fit



## Prediction

- ▶ MSE across years: 0.2022
- ▶ MSE from  $M=20$ : 0.1962
- ▶ Cross-validated  $M$ : 2
- ▶ Cross-validated MSE: 0.1912