



On Sparse Nonparametric Conditional Covariance Selection

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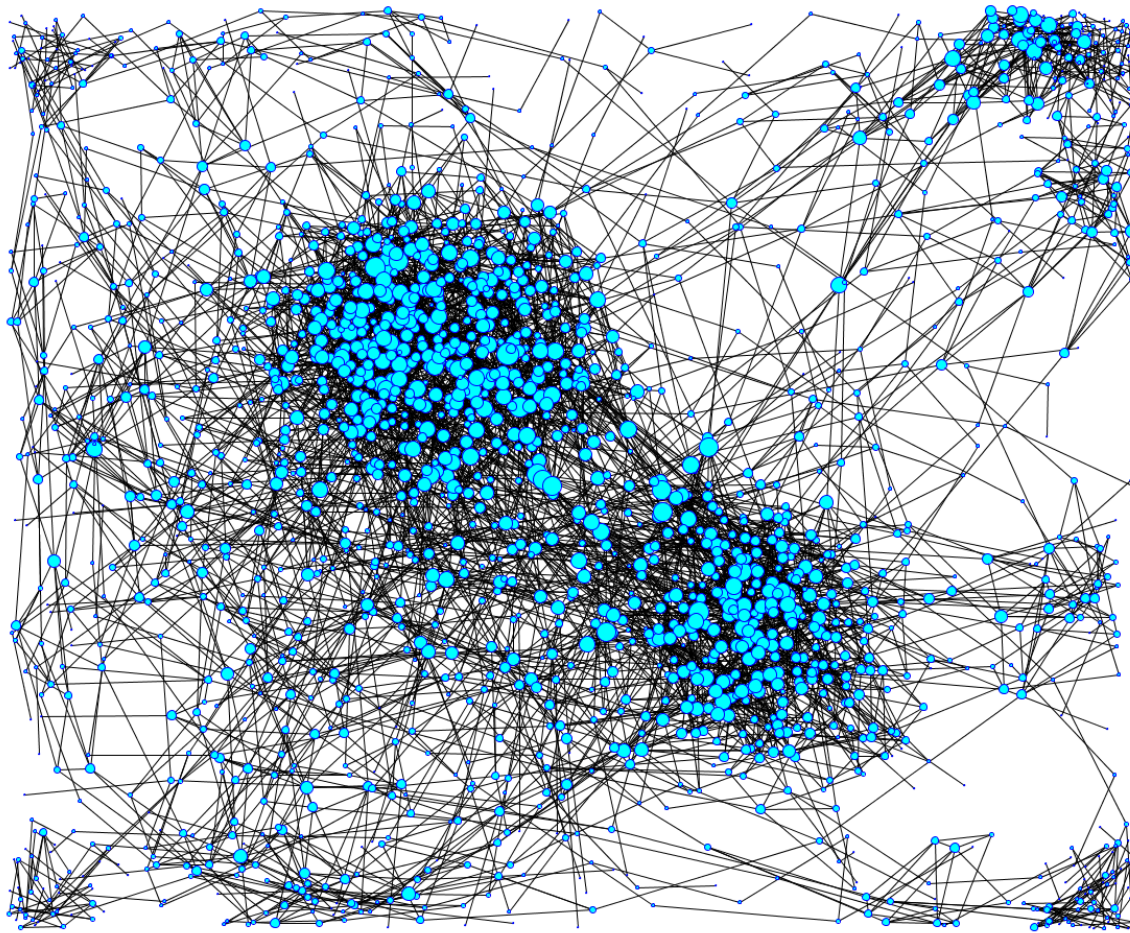
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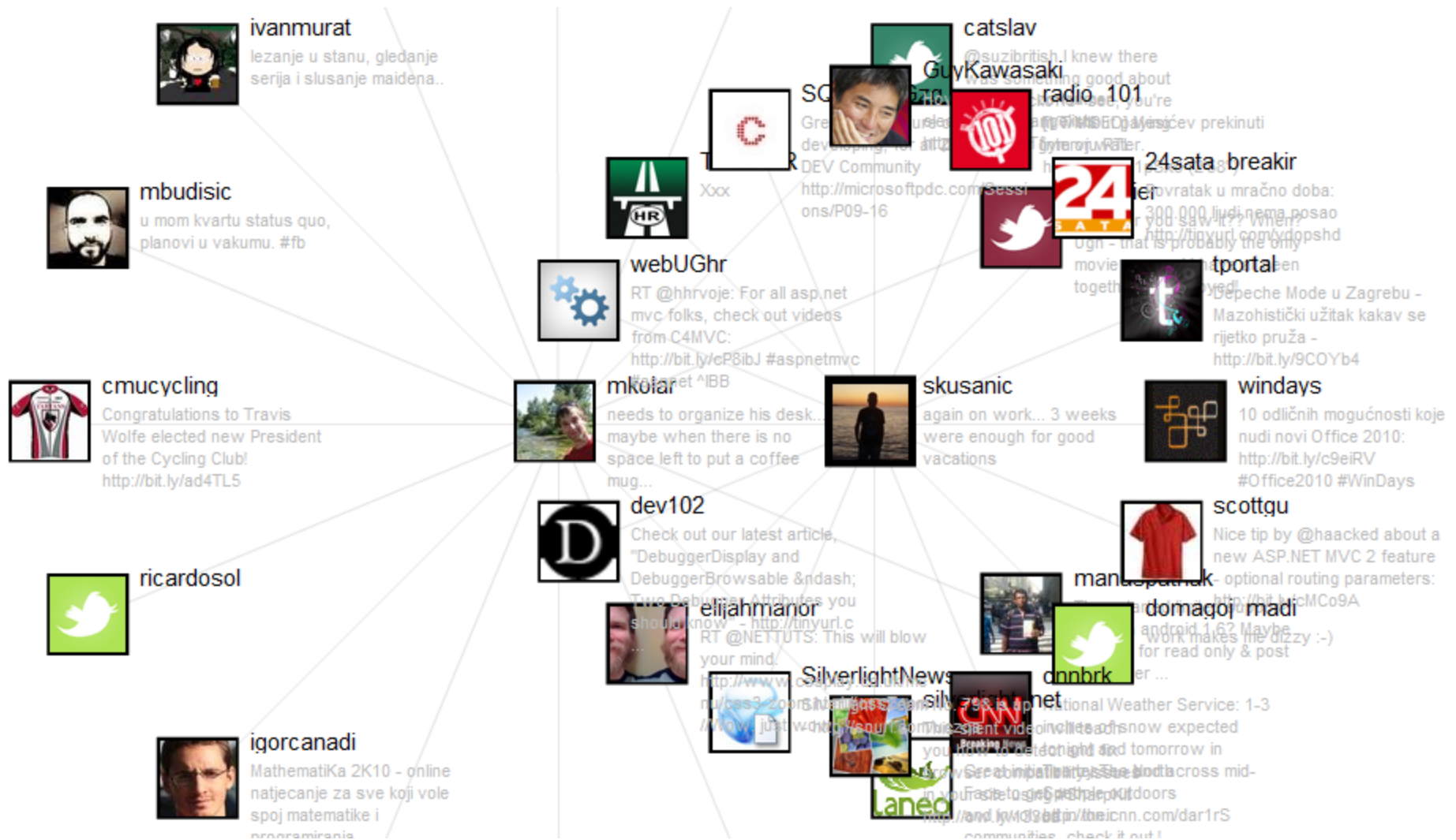
Estimating Associations among Variables

Important to many researchers in.....

Biology: Gene Regulatory Networks

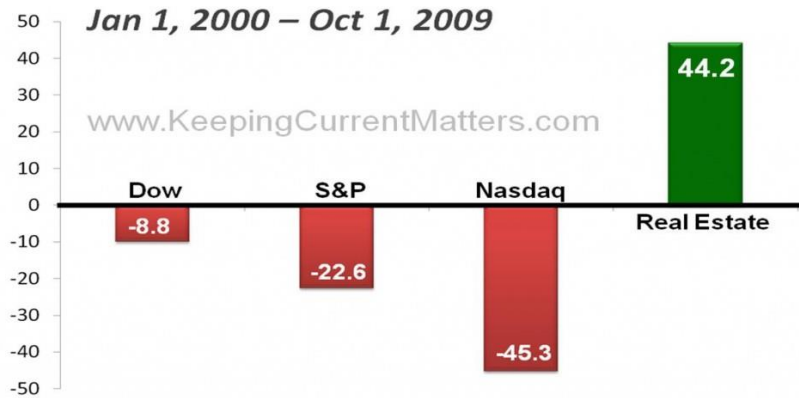


Social Networks: Twitter

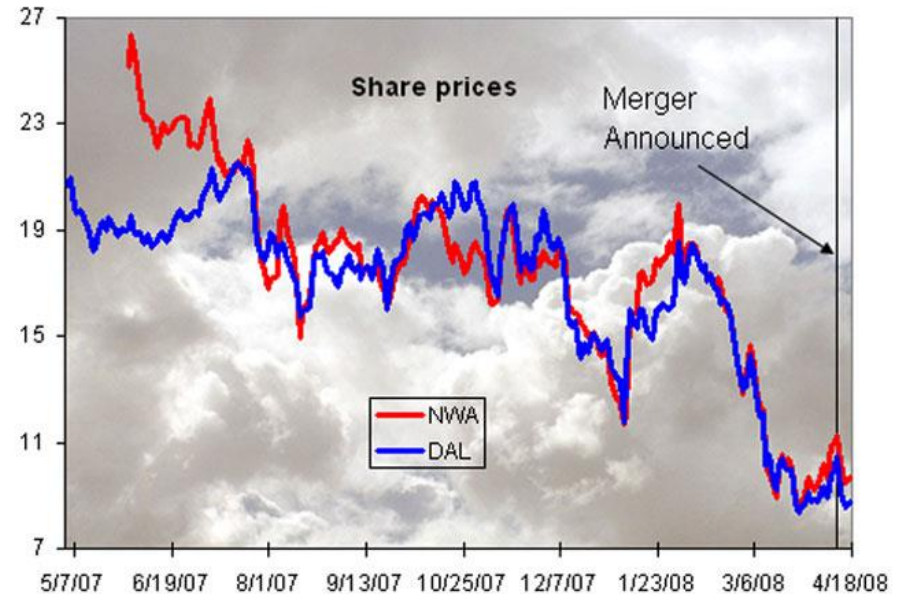


Finance: Stock Associations

Return on Investment



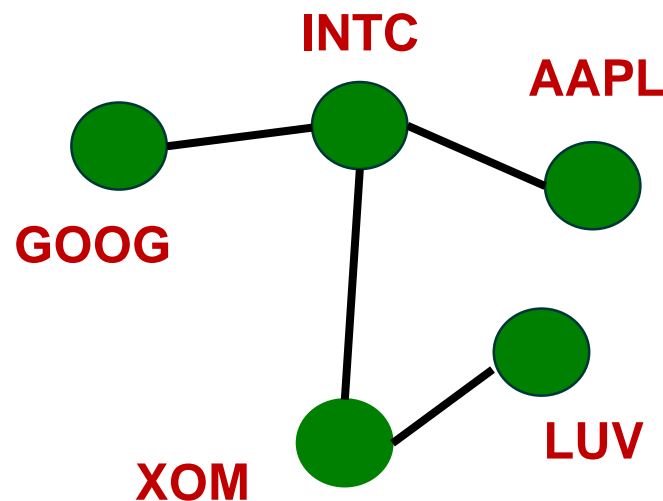
Source: MSN Money.com, Case Shiller



<http://minnesota.publicradio.org/display/web/2008/04/15/nwa2/>

Covariance Selection

- Assume data is iid and system is isolated
- Estimate non-zero elements of inverse covariance matrix
[Meinshausen, Buhlmann 06, Ravikumar et al. 08]
- Can be visualized as network where edges are non-zero precision matrix elements

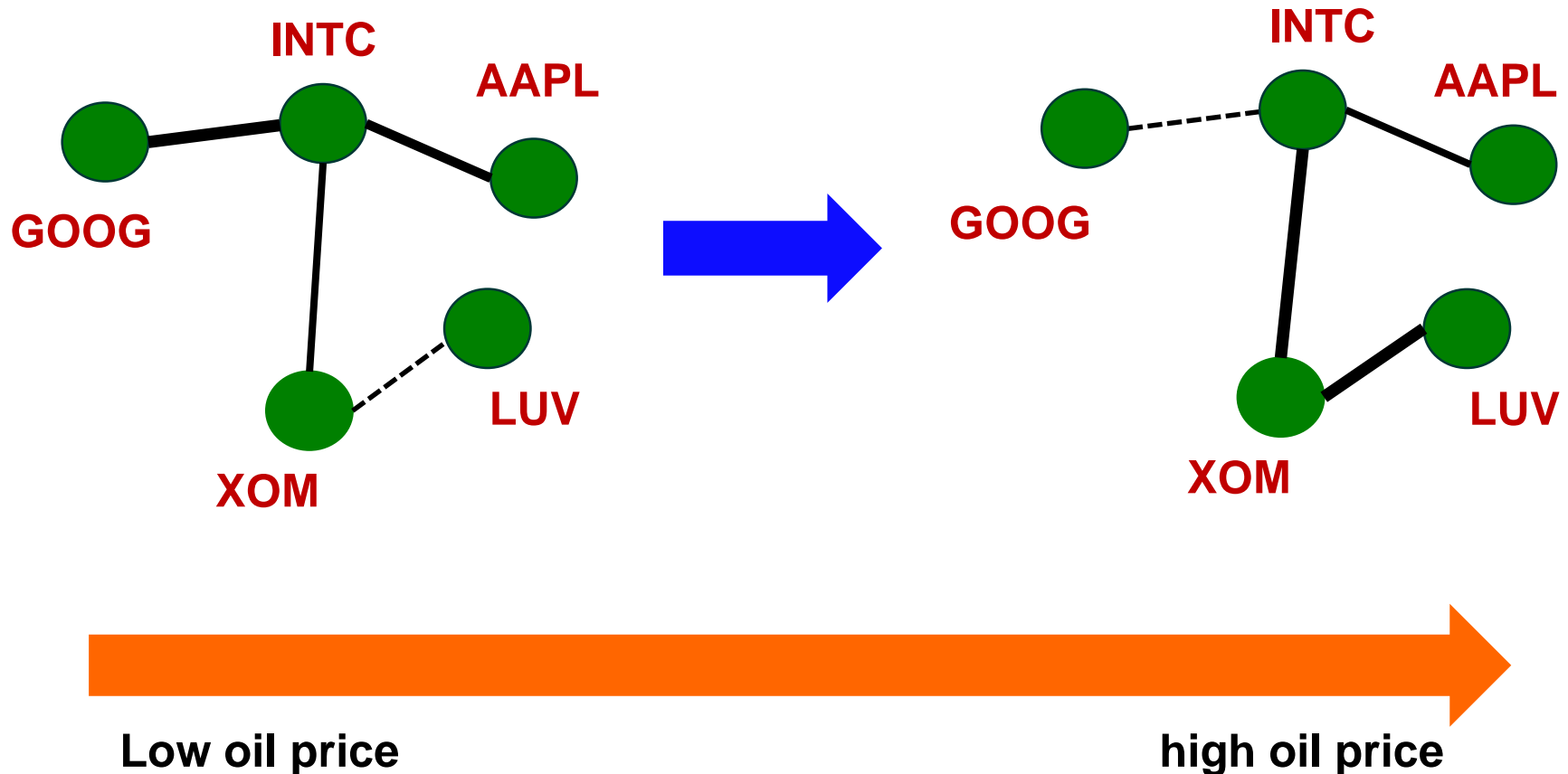


Environmental Variables

- More realistic to model the associations as **functions of the environment**
 - **Genes** in a regulatory network **conditioned on blood pressure**
 - **Stocks** in the NYSE **conditioned on economic indicator**
 - **People** in a social network **conditioned on time**
- Environmental variable can be **continuous** and **random**

Conditional Covariance Estimation

- Assume that set of edges remains fixed, but the values can change.



Conditional Covariance Estimation

$\mathbf{X} \in \mathbb{R}^p$ Set of variables (stocks)

$Z \in \mathbb{R}$ Environmental variable (oil price)

$\Sigma(z) := \text{Cov}(\mathbf{X} | Z = z)$ Conditional covariance matrix

$\Omega(z) := \Sigma(z)^{-1}$ Conditional precision matrix

**Goal is to select non-zero elements of
conditional precision matrix (network edges)**

Partial Correlation

- Partial Correlation - correlation between two variables conditioned on the rest

- Related to precision matrix elements

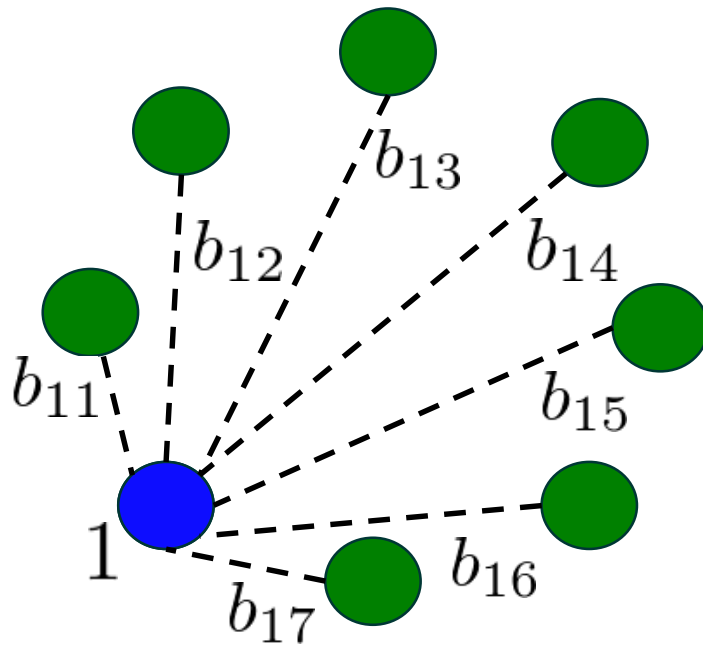
Precision matrix element

$$\rho_{uv}(z) = - \frac{\omega_{uv}(z)}{\sqrt{\omega_{uu}(z)\omega_{vv}(z)}}$$

Partial correlation coefficient

Neighborhood selection

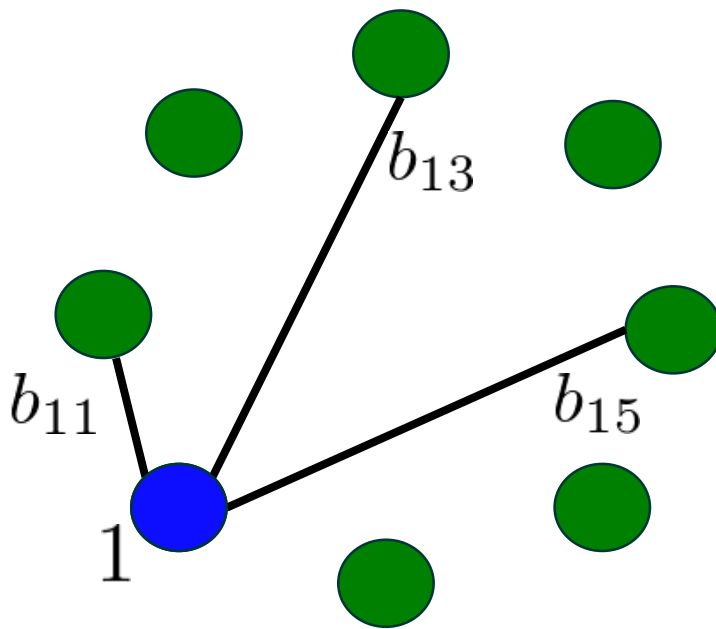
$$X_u = \sum_{v \neq u} X_v b_{uv}(z) + \epsilon_u(z), \quad u \in [p]$$



$$\rho_{uv}(z) = \text{sign}(b_{uv}(z)) \sqrt{b_{uv}(z)b_{vu}(z)}$$

Neighborhood selection

$$X_u = \sum_{v \neq u} X_v b_{uv}(z) + \epsilon_u(z), \quad u \in [p]$$

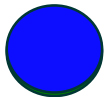


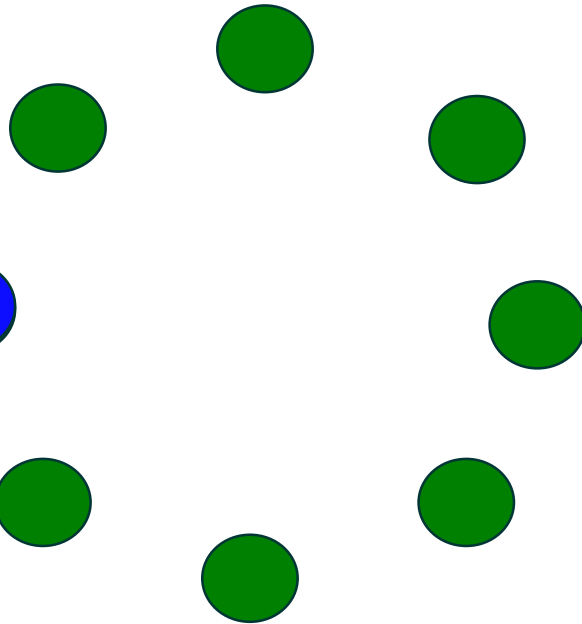
$$\rho_{uv}(z) = \text{sign}(b_{uv}(z)) \sqrt{b_{uv}(z)b_{vu}(z)}$$

Neighborhood selection

$$X_u = \sum_{v \neq u} X_v b_{uv}(z) + \epsilon_u(z), \quad u \in [p]$$

$$\rho_{uv}(z) = \text{sign}(b_{uv}(z)) \sqrt{b_{uv}(z) b_{vu}(z)}$$

2 



Loss Function

$$\mathcal{L}_u(\mathbf{B}_u; \mathcal{D}^n) :=$$

$$\sum_{z \in \{z^j\}_{j \in [n]}} \sum_{i \in [n]} \left(x_u^i - \sum_{v \neq u} x_v^i b_{uv}(z) \right)^2 K_h(z - z^i)$$

$$+ 2\lambda \sum_{v \neq u} \sqrt{\sum_{z \in \{z^j\}_{j \in [n]}} b_{uv}(z)^2}$$

RSS: residual
sum of squares

Kernel: smooth
across z

Group penalty:
fixed set of non-
zero elements

Determining Structure

Structure is fixed for all \mathbf{z} , so

$$\hat{S} := \{(u, v) : \max\{\|\hat{b}_{uv}(\cdot)\|_2, \|\hat{b}_{vu}(\cdot)\|_2\} > 0\}$$

Optimization

- Modified active shooting algorithm /coordinate descent [Friedman et al. 2010]
- Optimize one group while holding others fixed.

$$\begin{aligned} \mathcal{L}_u^v(\{b_{uv}(z^j)\}_{j \in [n]}; \mathcal{D}^n) := \\ \sum_{z \in \{z^j\}_{j \in [n]}} \sum_{i \in [n]} (r_{uv}^i(z) - x_v^i b_{uv}(z))^2 K_h(z - z^i) \\ + 2\lambda \|b_{uv}(\cdot)\|_2, \end{aligned}$$

$$r_{uv}^i(z) = x_u^i - \sum_{v' \neq u, v} x_{v'}^i \tilde{b}_{uv'}(z)$$

Optimization

- Fast way to check if group is zero

$$\frac{1}{\lambda^2} \sum_{z \in \{z^j\}_{j \in [n]}} \left(\sum_{i \in [n]} x_v^i r_{uv}^i(z) K_h(z - z^i) \right)^2 \leq 1.$$

- Otherwise optimize block (i.e. using gradient descent)

Consistent Structure Estimation

Let $h = \mathcal{O}(n^{-1/5})$, $\lambda = \mathcal{O}(n^{7/10}\sqrt{\log p})$ and $n^{-9/5}\lambda \rightarrow 0$.

If $\frac{n^{11/10}}{\sqrt{\log p}} \min_{u,v \in S} \|b_{uv}(\cdot)\|_2 \rightarrow \infty$, then $\mathbb{P}[\hat{S} = S] \rightarrow 1$.

Selecting Regularization

$$\text{BIC}_u(\lambda) = \log(\text{RSS}_u(\lambda)) + \frac{\hat{d}f_{u,\lambda}(\log(nh) + 2\log p)}{nh}$$

log residual sum of squares

Number of non-zero elements in row

Extra penalty (Chen & Chen 08)

Selecting Regularization

$$\hat{\lambda} = \operatorname{argmin}_{\lambda} \sum_{u \in [p]} \operatorname{BIC}_u(\lambda)$$

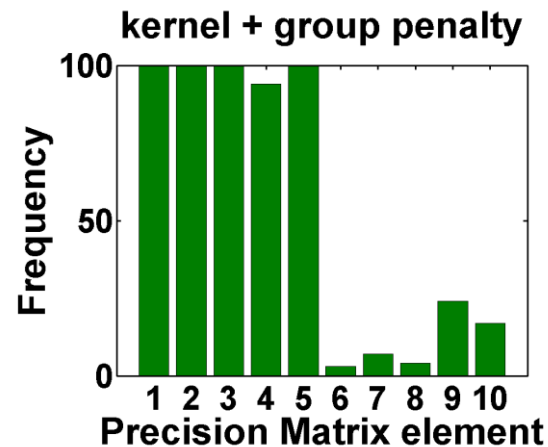
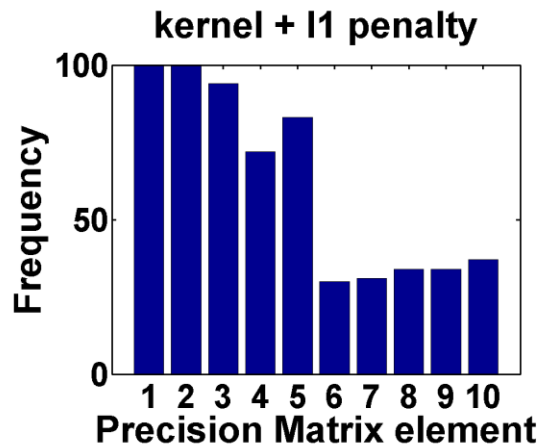
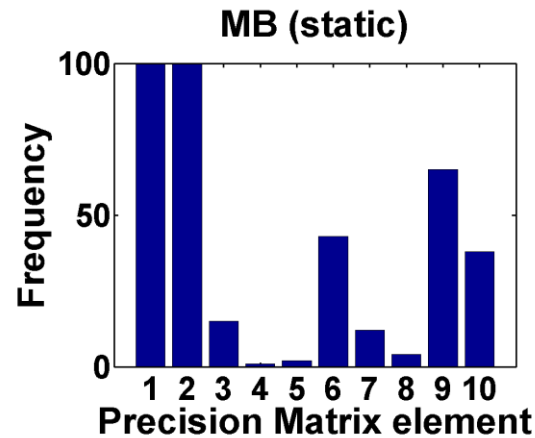
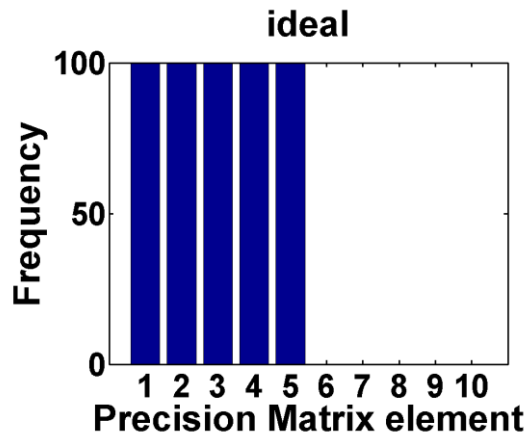
$$\mathbb{P}[\hat{S}(\hat{\lambda}) = S] \rightarrow 1.$$

Simulations: A Toy Example

- 1) Constant
- 2) Constant
- 3) Piecewise Constant
- 4) Linear
- 5) Sinusoid

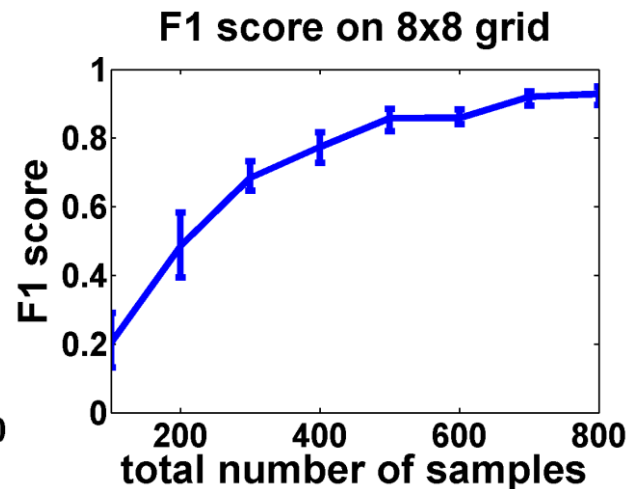
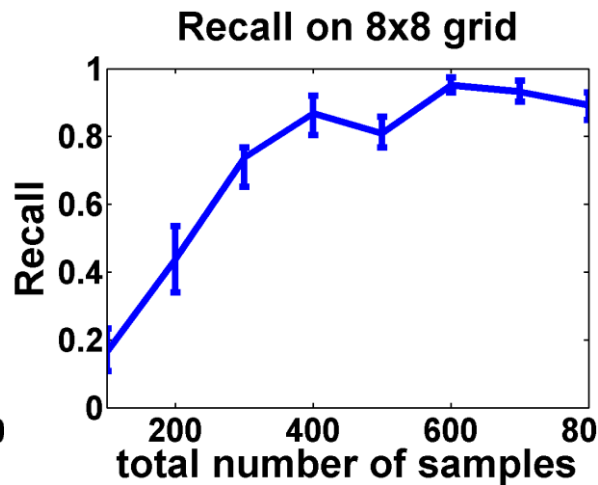
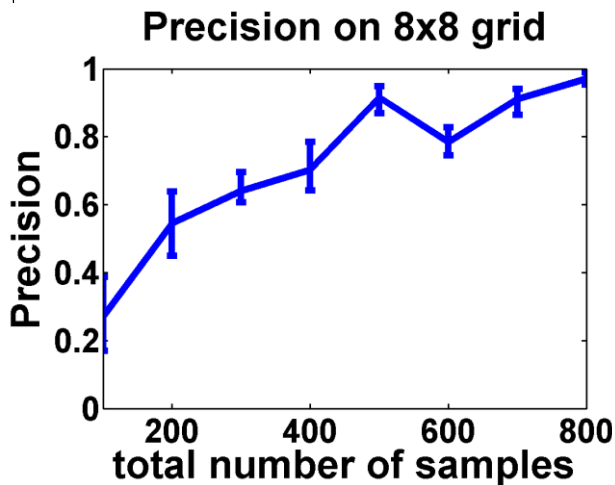
$$\Omega(z) = \begin{bmatrix} & 1 & & & 4 \\ & & & & \\ 1 & & & & \\ & & 3 & & \\ & & & 2 & \\ 4 & & & & \\ & & 5 & & \\ & & & 2 & \\ & & & & 3 \\ & & & & & 5 \\ & & & & & & 2 \\ & & & & & & & 4 \end{bmatrix}$$

Toy Example Results



Larger Simulations

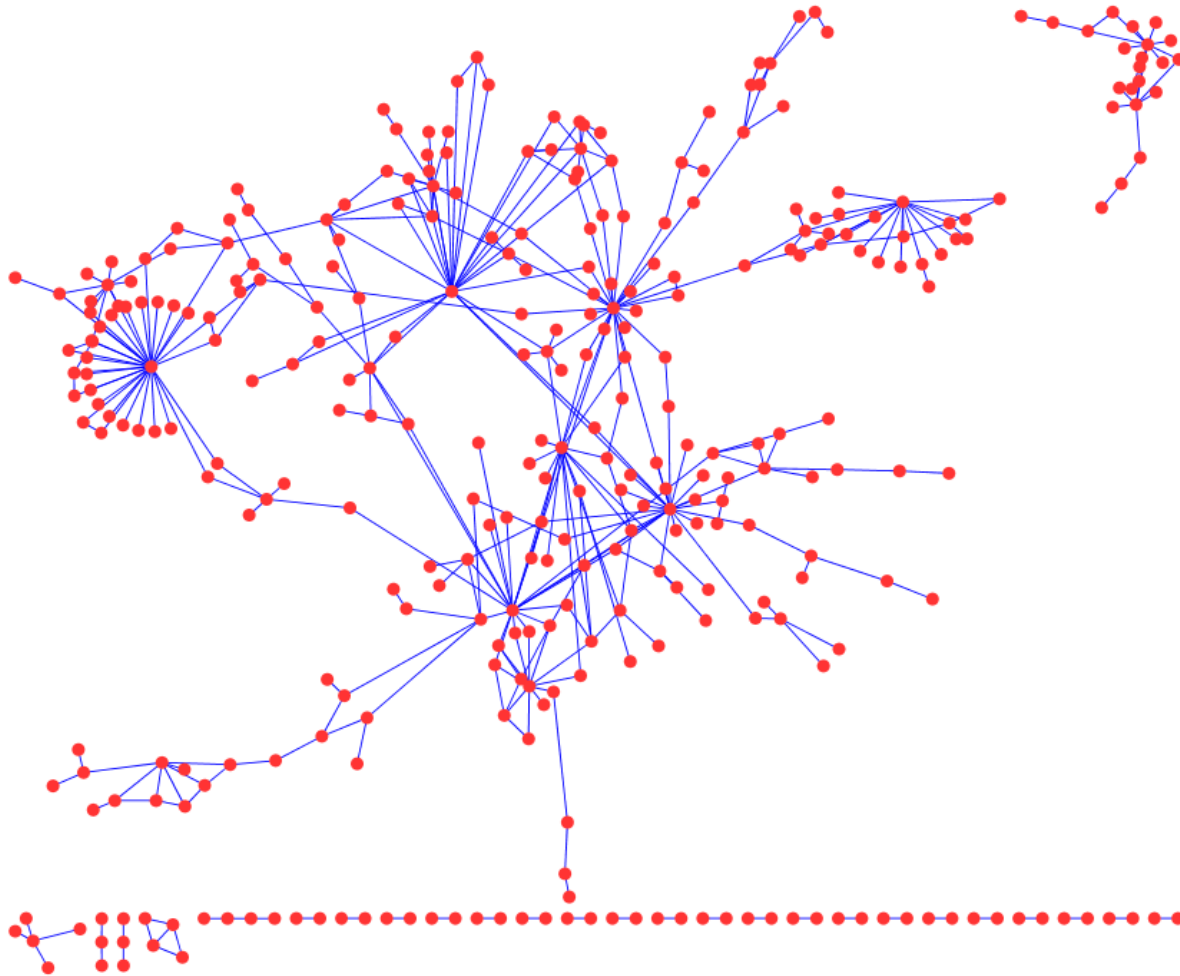
- 8x8 grid
- All non-zero precision matrix elements are sinusoids.



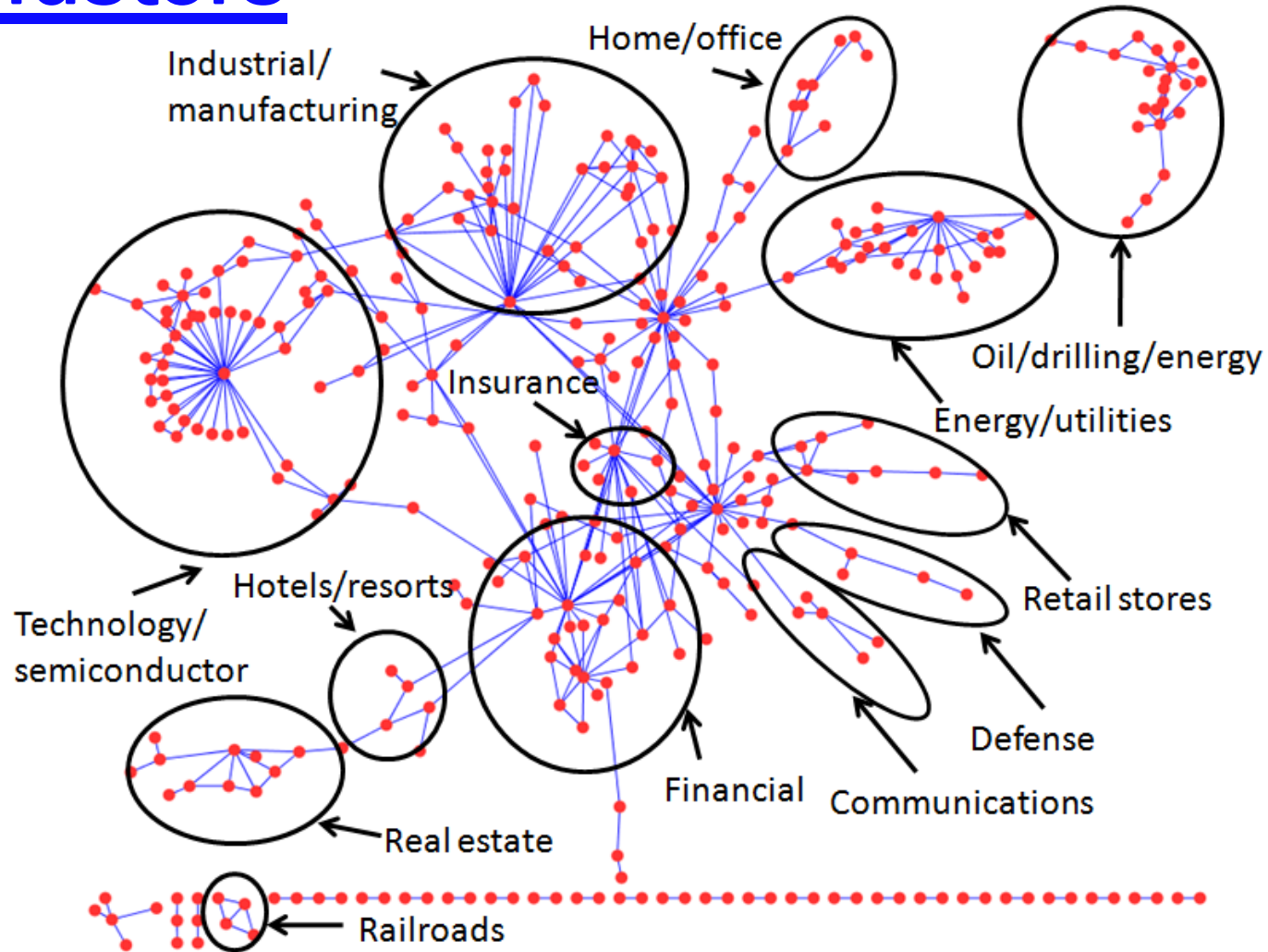
Analyzing the S&P 500

- Examine associations among stocks
 - Help an economist studying the market
 - Assist an investor building a diverse portfolio
- Stock prices from Jan 1, 2003 – Dec 31, 2005.
- Condition on oil price, an economic indicator

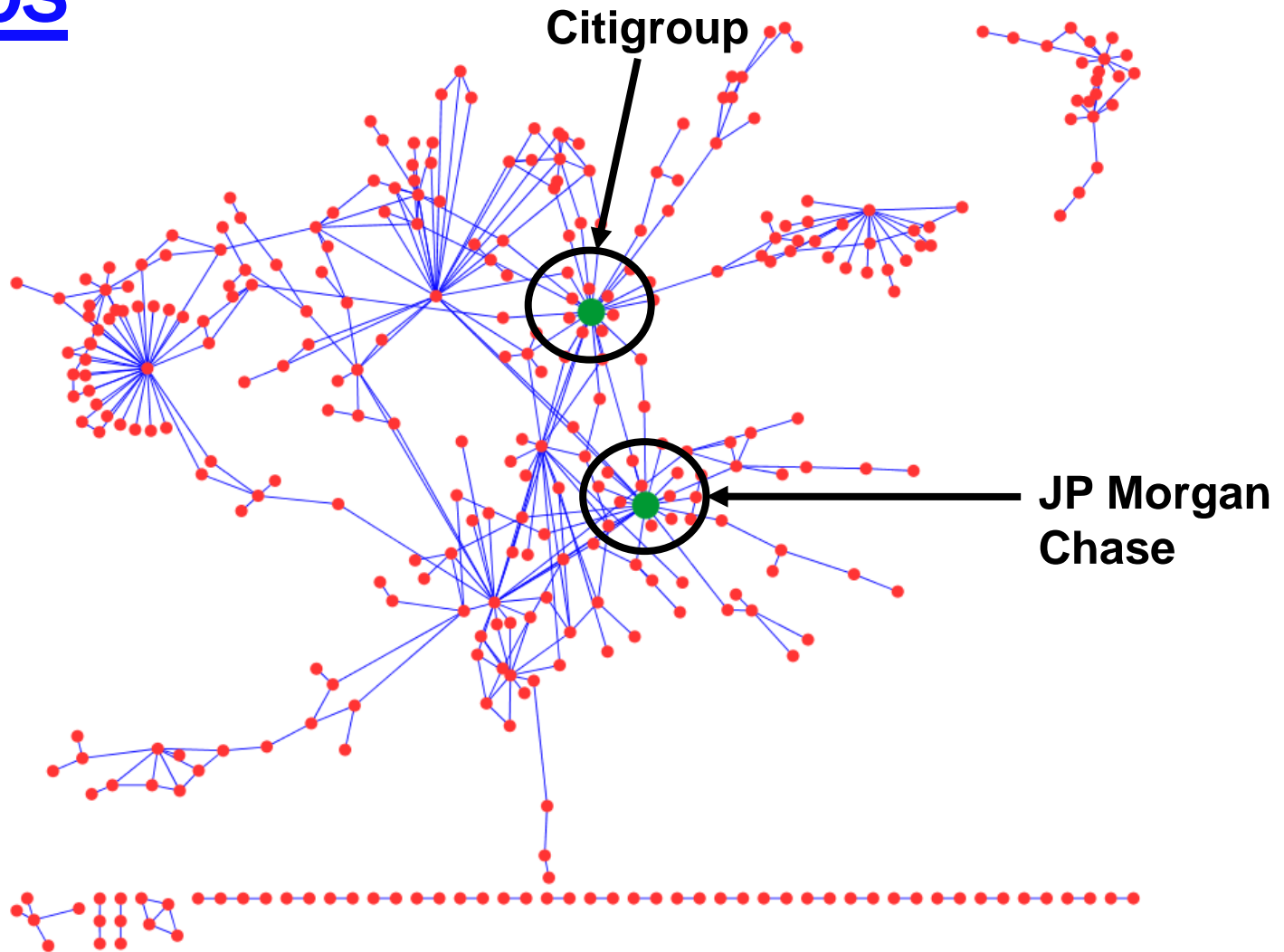
Network



Clusters

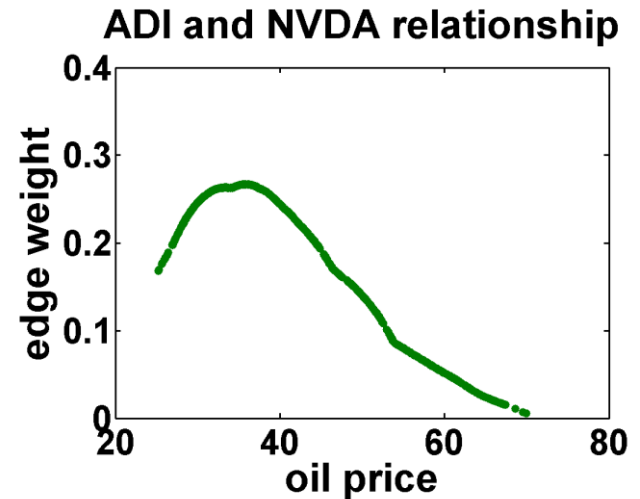
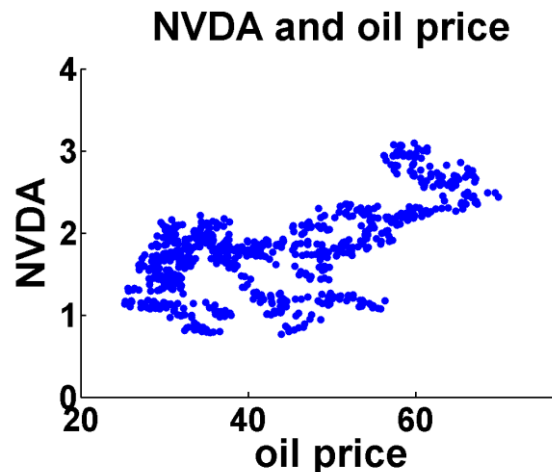
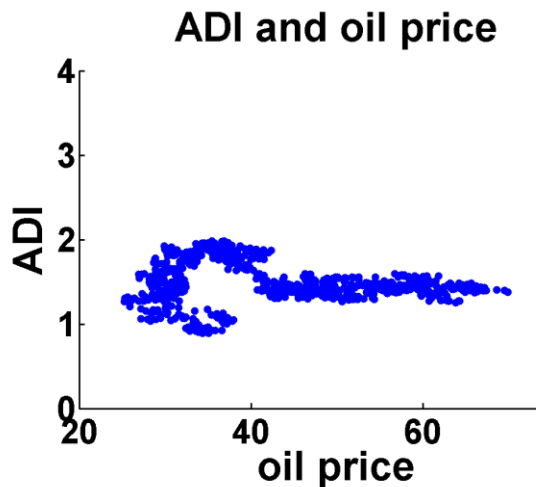


Hubs



Edge Weights

- Edge weights (proportional to partial correlations) reflect changes in associations.



Discussion

- Estimate associations among variables conditioned on the environment
- Applicable to biology, finance, social networks etc.
- Our method is simple, nonparametric, and works well in high dimensions

Acknowledgements



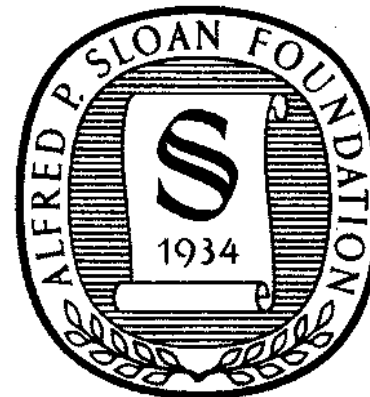
ONR



NSF



NIH



**Alfred P. Sloan
Fellowship to EPX**

Thank you!