

Communities in statistically-validated networks

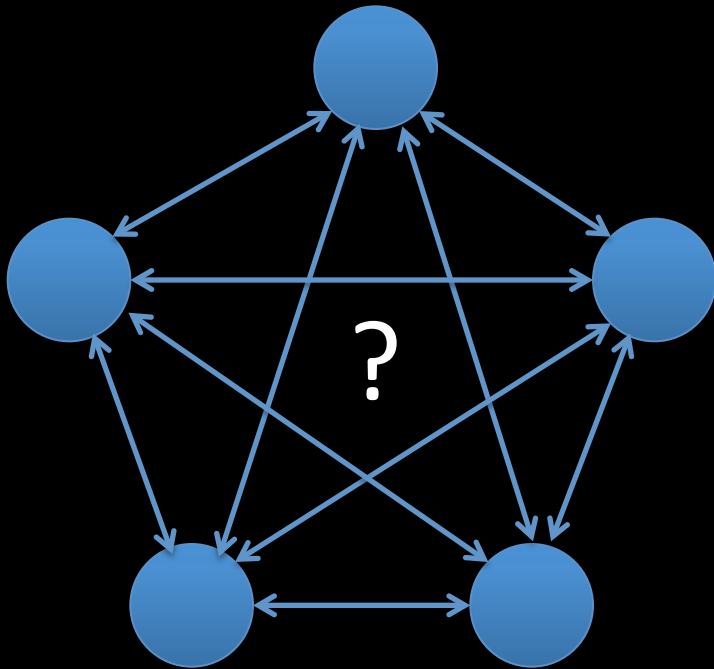
Chester Curme

In collaboration with:

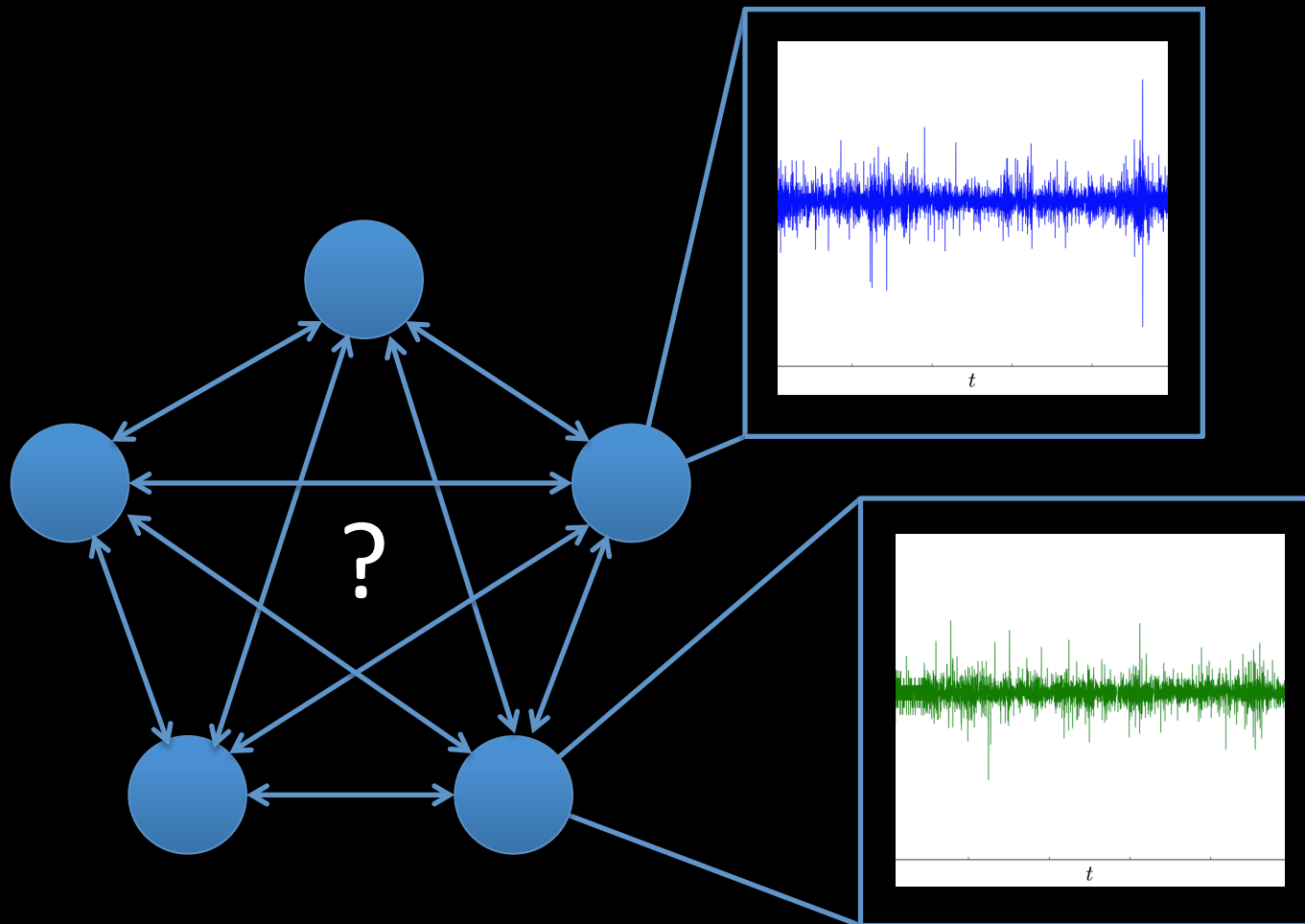
Irena Vodenska

H. Eugene Stanley

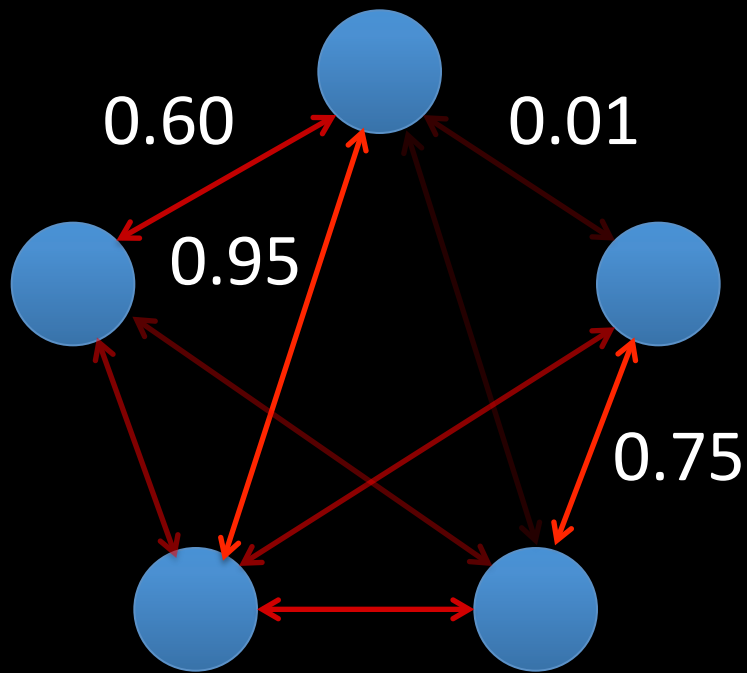
Big picture



Big picture

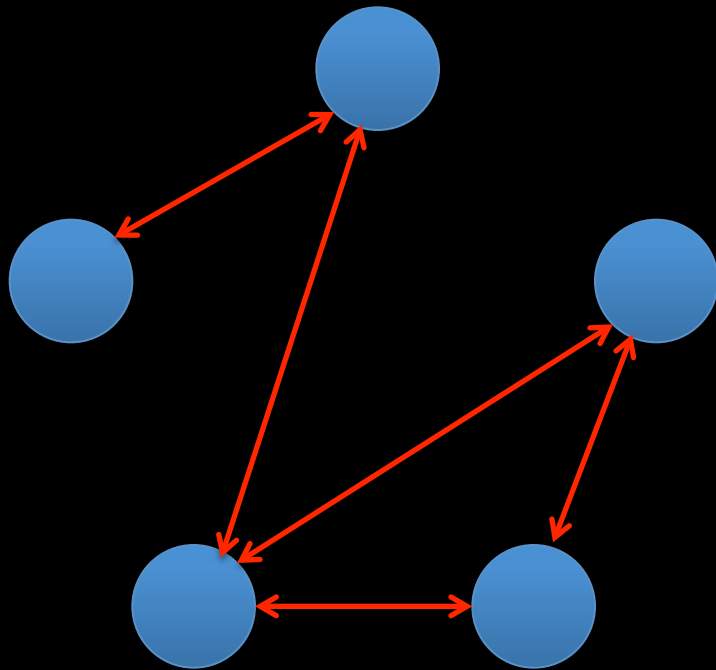


Big picture



$$A = \begin{bmatrix} 1 & 0.60 & 0.01 & 0.95 & \dots \\ 0.60 & 1 & \dots & \dots & \dots \\ 0.01 & \dots & 1 & \dots & 0.75 \\ 0.95 & \dots & \dots & 1 & \dots \\ \dots & \dots & 0.75 & \dots & 1 \end{bmatrix}$$

Big picture



$$A = \begin{bmatrix} 0 & 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 \\ 1 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 1 & 0 \end{bmatrix}$$

Thesis overview

Focus on one experimental setting:

- Associate time series to nodes

Thesis overview

Focus on one experimental setting:

- Associate time series to nodes
- Interactions measured by lagged correlations
 - A is asymmetric

Thesis overview

Focus on one experimental setting:

- Associate time series to nodes
- Interactions measured by lagged correlations
 - A is asymmetric
- Low signal-to-noise
 - Statistical uncertainty is important

Thesis overview

1) Methodology and applications

- Curme, Tumminello, Mantegna, Stanley, Kenett. *Quantitative Finance* (2014).

2) Extend to seasonal time series and use to explain a phenomenon in financial markets

- Curme, Tumminello, Mantegna, Stanley, Kenett (in preparation).

3) Relate community structures to statistical model performance

- Curme, Vodenska, Stanley (submitted).

4) Using topic models to explain market movements

- Curme, Zhuo, Moat, Preis (in preparation).
- Curme, Preis, Stanley, Moat. *PNAS* (2014).
- Moat, Curme, Avakian, Kenett, Stanley, Preis. *Scientific Reports* (2013).
- Moat, Curme, Stanley, Preis. Book chapter in *Nonlinear phenomena in complex systems: from nano to macro scale* (2014).

Thesis overview

1) Methodology and applications

- Curme, Tumminello, Mantegna, Stanley, Kenett. *Quantitative Finance* (2014).

2) Extend to seasonal time series and use to explain a phenomenon in financial markets

- Curme, Tumminello, Mantegna, Stanley, Kenett (submitted).

3) Relate community structures to statistical model performance

- Curme, Vodenska, Stanley (submitted).

4) Using topic models to explain market movements

- Curme, Zhuo, Moat, Preis (submitted).
- Curme, Preis, Stanley, Moat. *PNAS* (2014).
- Moat, Curme, Avakian, Kenett, Stanley, Preis. *Scientific Reports* (2013).
- Moat, Curme, Stanley, Preis. Book chapter in *Nonlinear phenomena in complex systems: from nano to macro scale* (2014).

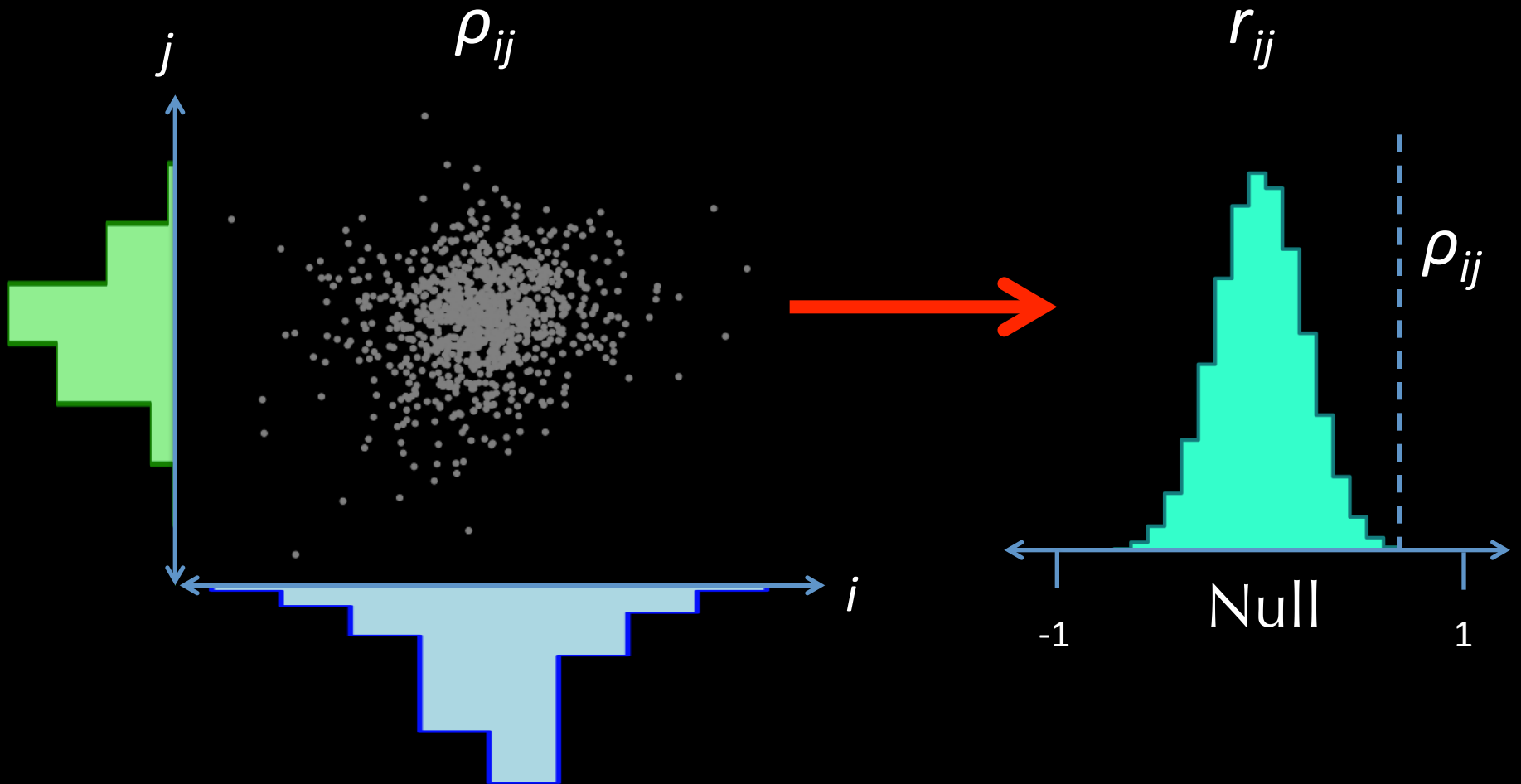
Data

Market returns

News sentiments



Statistical validation



Statistically-validated network

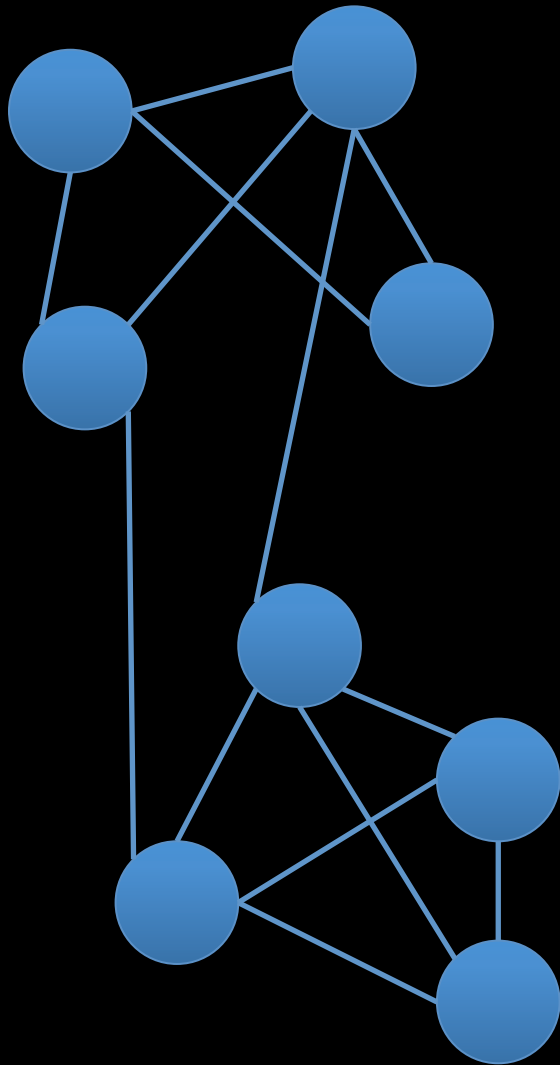


Statistically-validated network



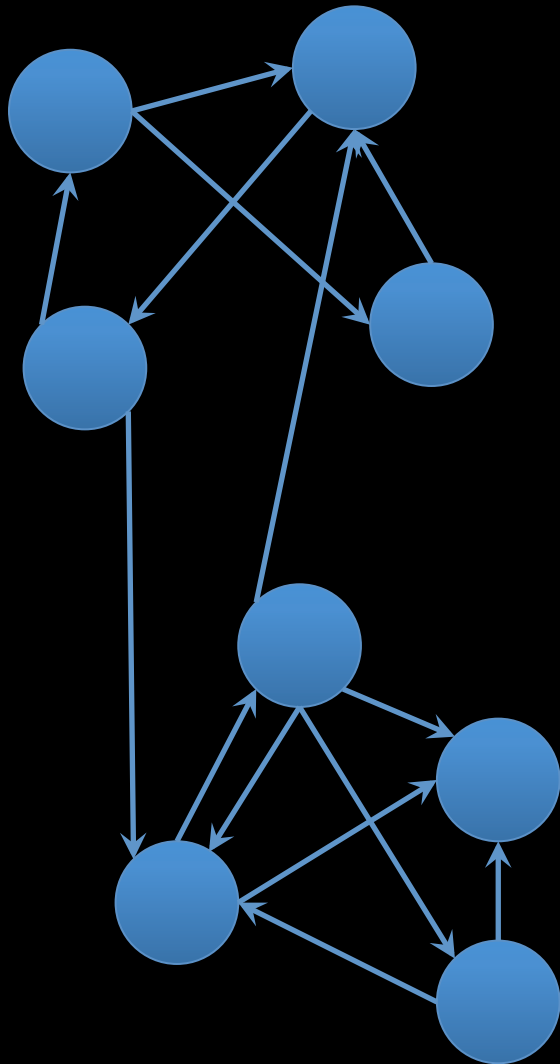
News → Markets: 12 links
Markets → News: 174 links

Community Structures



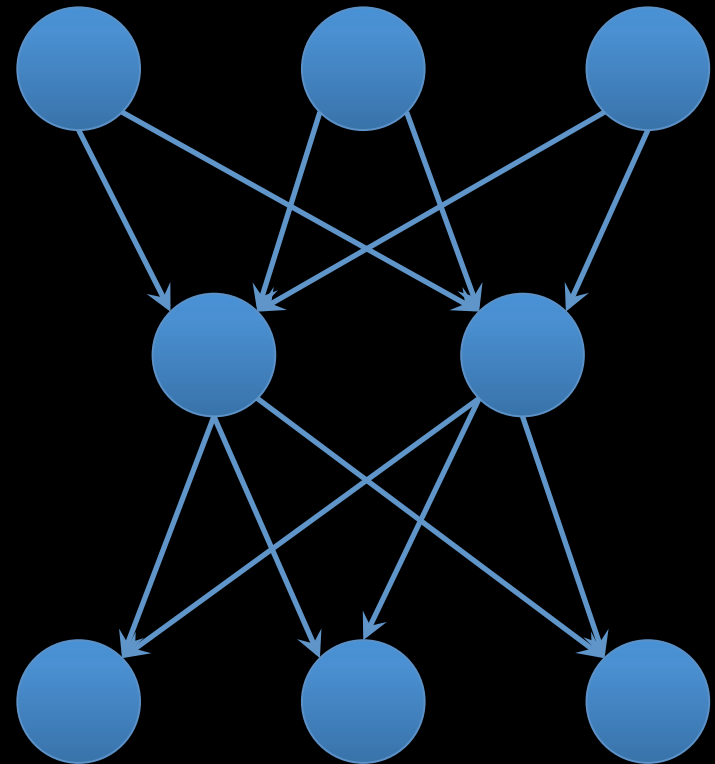
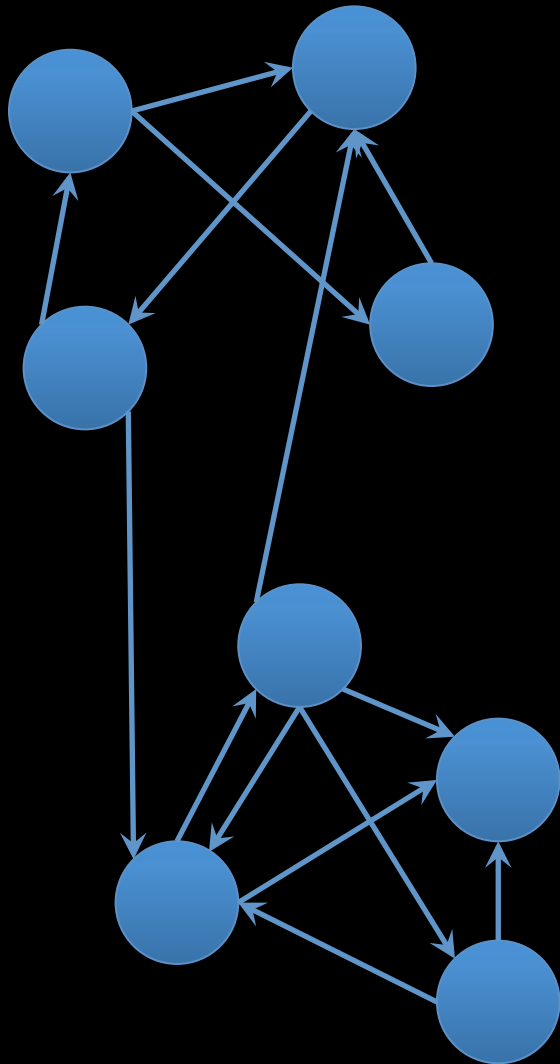
In undirected networks...

Community Structures



In directed networks...

Community Structures

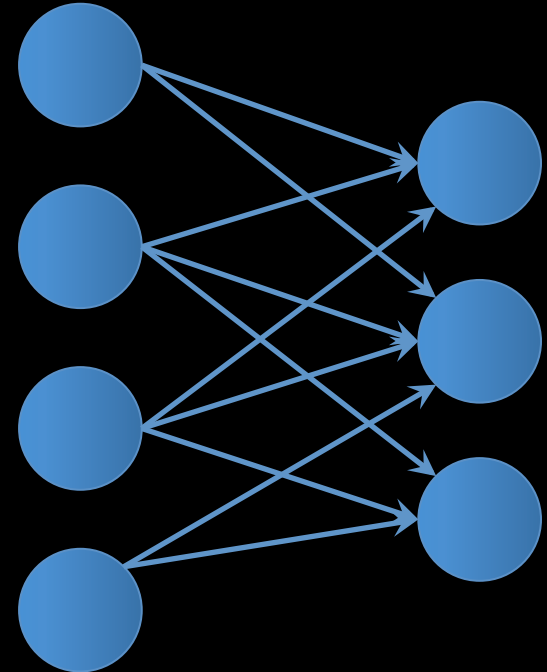


In directed networks...

Finding bipartite substructure

Singular value decomposition:

$$A = U \Sigma V^T$$



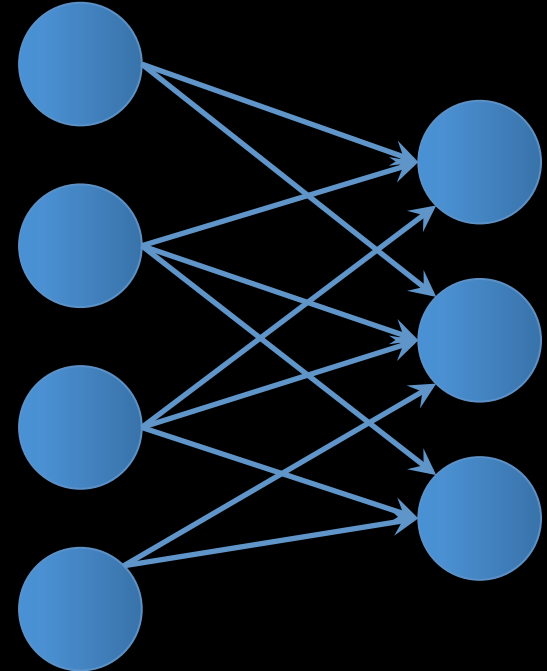
Finding bipartite substructure

Singular value decomposition:

$$A = U \Sigma V^T$$

↙
 $\left[\begin{array}{c} \text{Eigenvectors} \\ \text{of } AA^T \end{array} \right]$

“Left singular
vectors”



Finding bipartite substructure

Singular value decomposition:

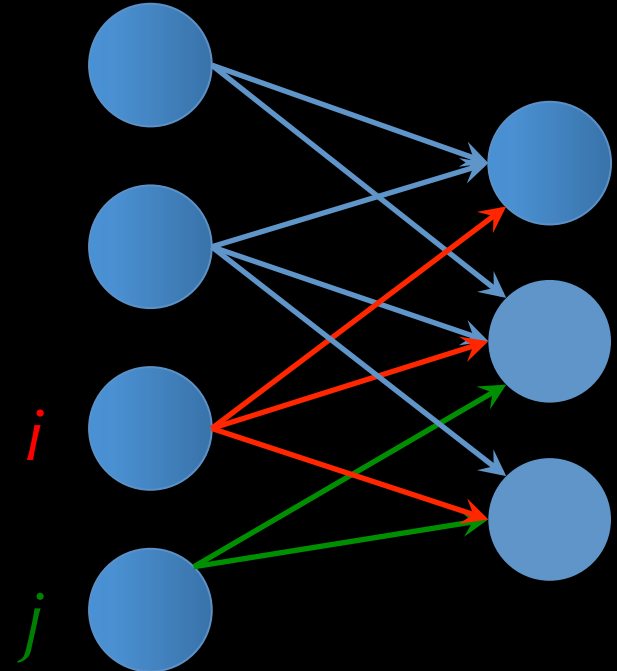
$$A = U \Sigma V^T$$

Eigenvectors
of AA^T

“Left singular
vectors”

$$AA^T =$$

$$\begin{matrix} & & i & j \\ \begin{matrix} i \\ j \end{matrix} & \begin{bmatrix} \dots & \color{red}{1} & \color{red}{1} & \color{red}{1} & \dots \\ \dots & 0 & \color{green}{1} & \color{green}{1} & \dots \end{bmatrix} & \begin{bmatrix} \vdots & \color{red}{1} & \color{red}{1} & \color{red}{1} & \vdots \\ \vdots & \color{green}{1} & \color{green}{1} & \color{green}{1} & \vdots \end{bmatrix} \end{matrix}$$



Finding bipartite substructure

Singular value decomposition:

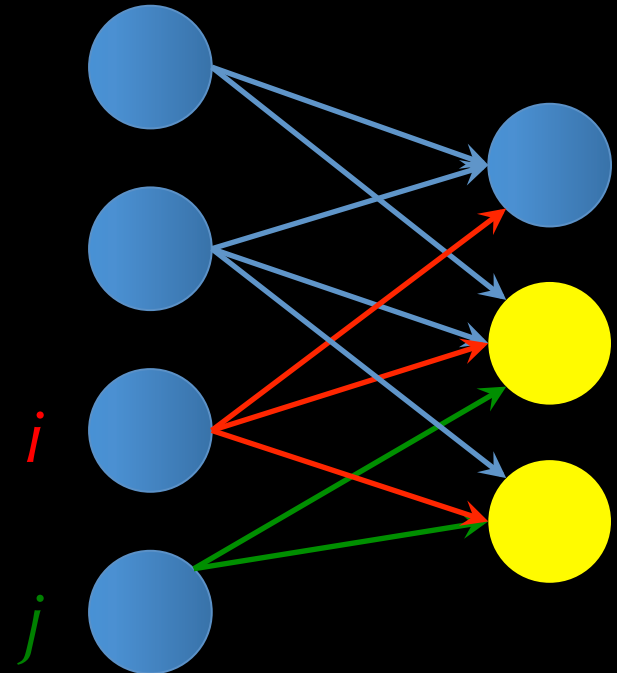
$$A = U \Sigma V^T$$

Eigenvectors
of AA^T

“Left singular
vectors”

$$AA^T =$$

$$\begin{matrix} & i & j \\ i & \begin{bmatrix} \dots, 2, \dots \end{bmatrix} \\ j & \begin{bmatrix} \dots, 2, \dots \end{bmatrix} \end{matrix}$$



Finding bipartite substructure

Singular value decomposition:

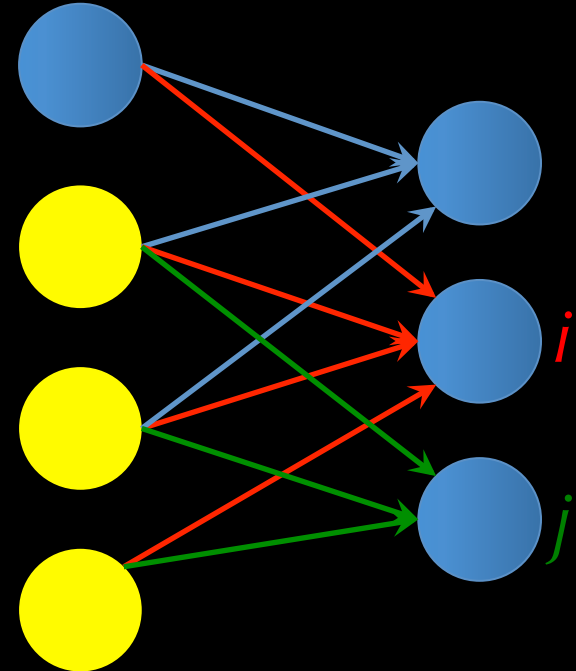
$$A = U \Sigma V^T$$

Eigenvectors
of AA^T

“Left singular
vectors”

Eigenvectors
of $A^T A$

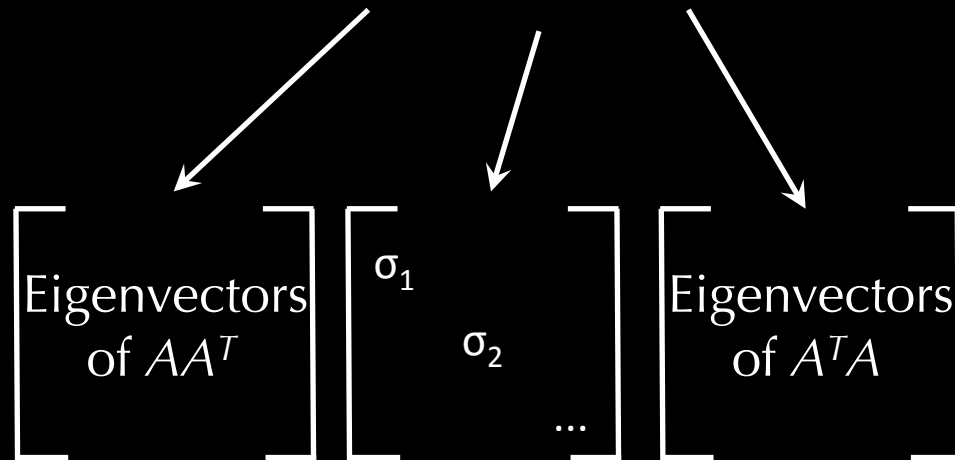
“Right singular
vectors”



Finding bipartite substructure

Singular value decomposition:

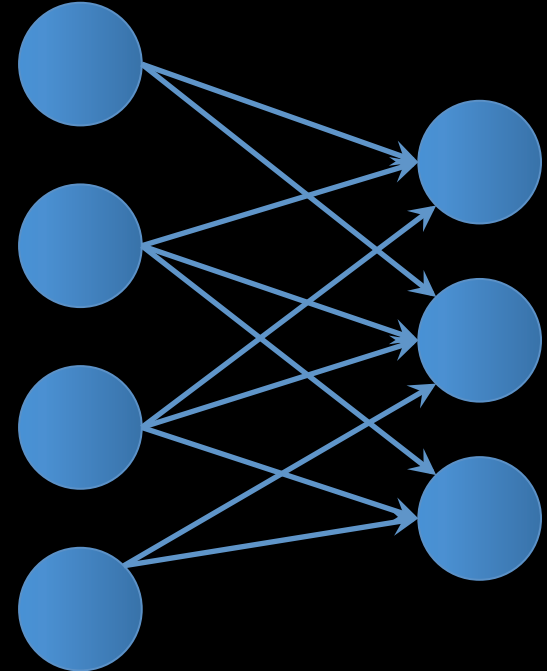
$$A = U \Sigma V^T$$


$$\begin{bmatrix} \text{Eigenvectors} \\ \text{of } AA^T \end{bmatrix} \begin{bmatrix} \sigma_1 \\ \sigma_2 \\ \dots \end{bmatrix} \begin{bmatrix} \text{Eigenvectors} \\ \text{of } A^T A \end{bmatrix}$$

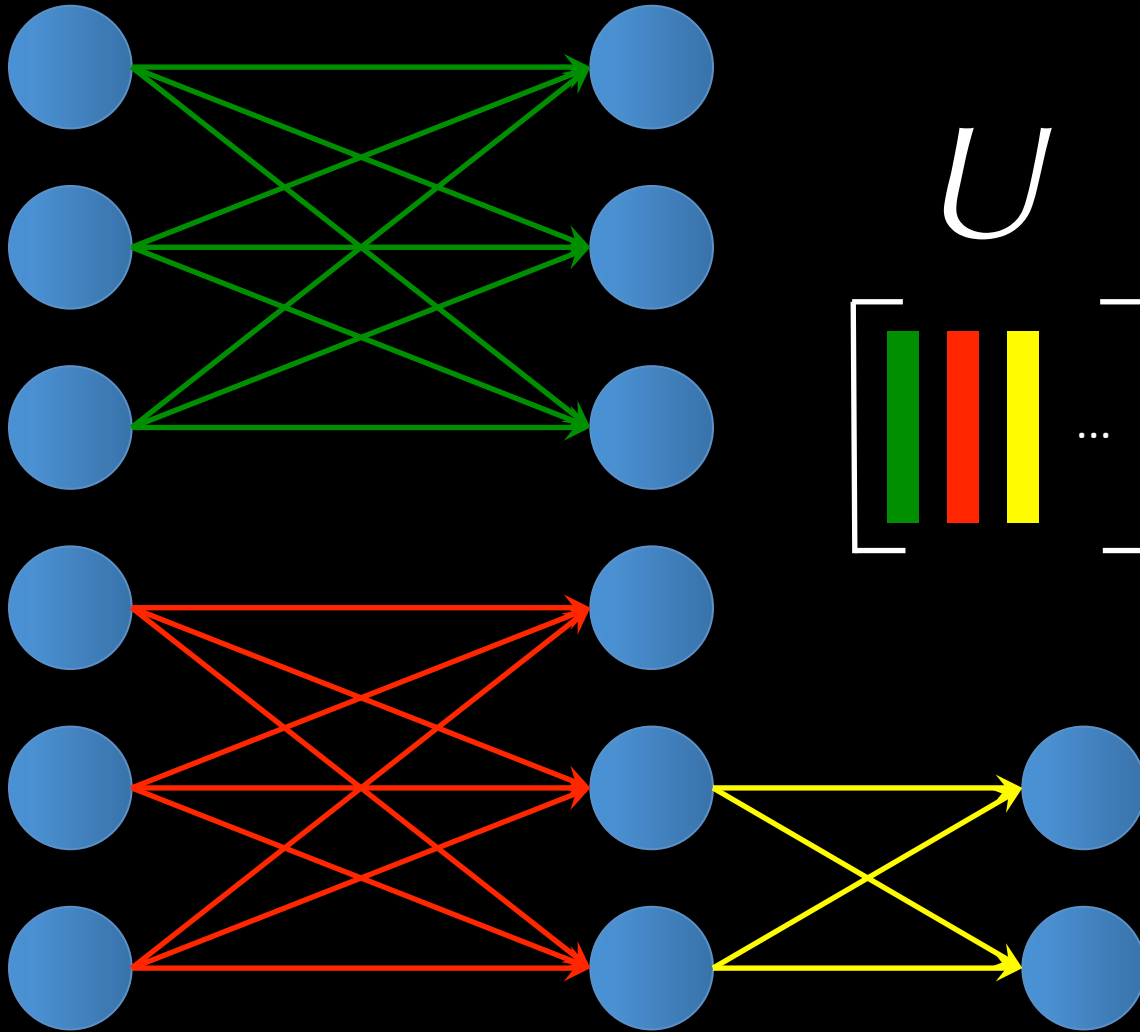
“Left singular
vectors”

“Singular
values”

“Right singular
vectors”

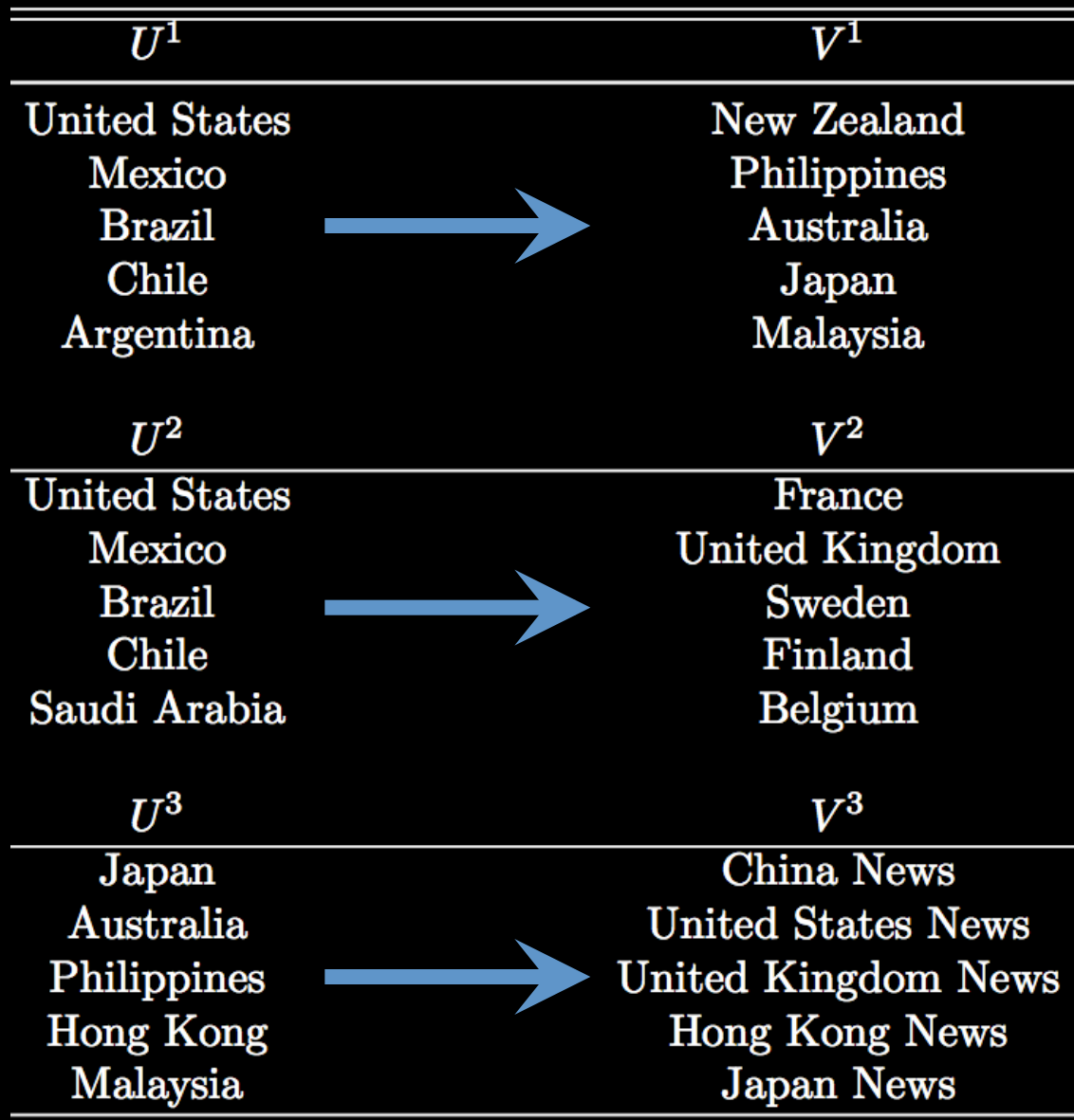


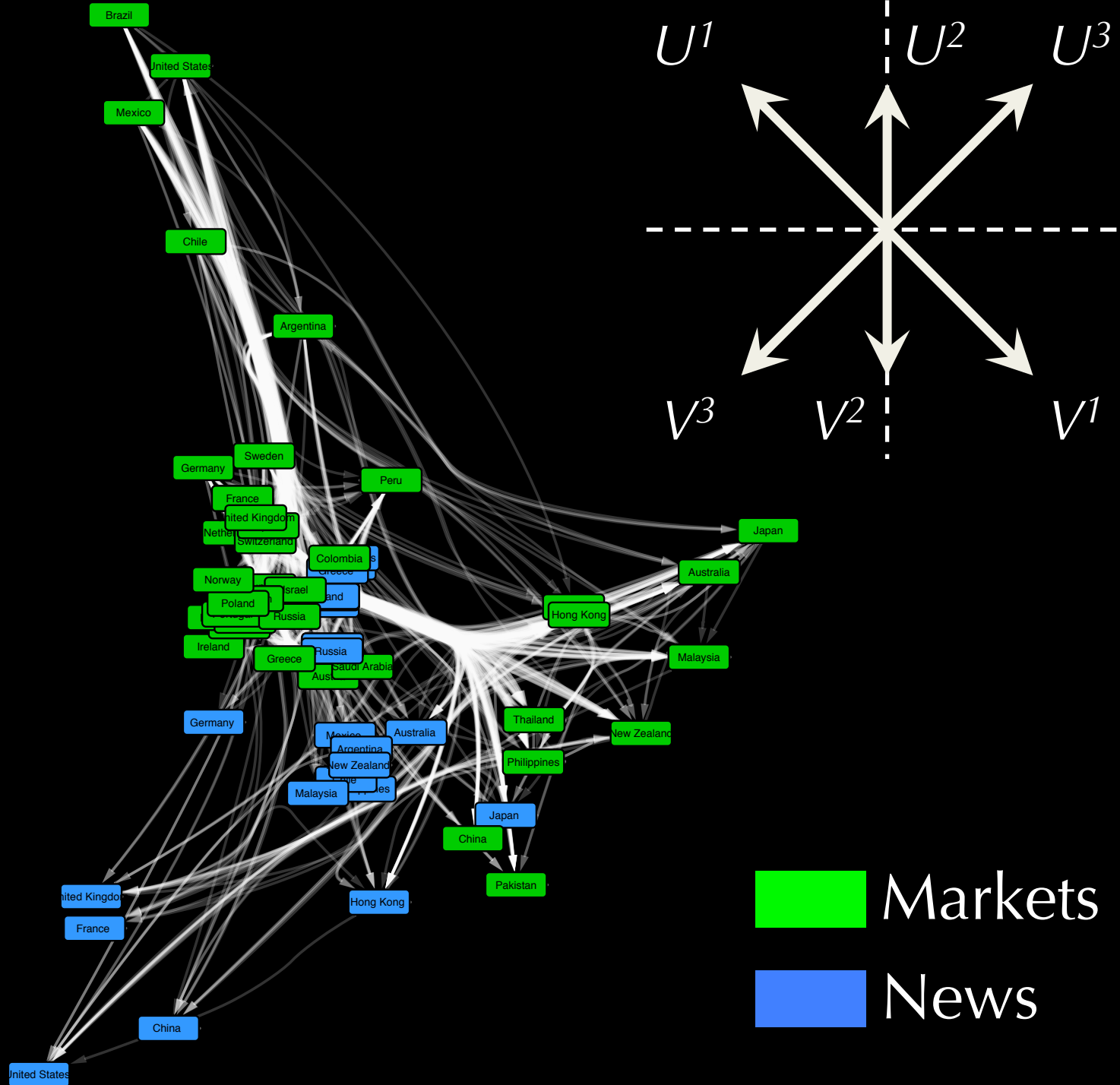
Finding bipartite substructure



$$U \quad \Sigma \quad V^T$$
$$\begin{bmatrix} \text{green bar} & \text{red bar} & \text{yellow bar} & \dots \end{bmatrix} \begin{bmatrix} \sigma_1 & & \\ & \sigma_2 & \\ & & \dots \end{bmatrix} \begin{bmatrix} \text{green bar} \\ \text{red bar} \\ \text{yellow bar} \\ \vdots \end{bmatrix}$$

Finding bipartite substructure





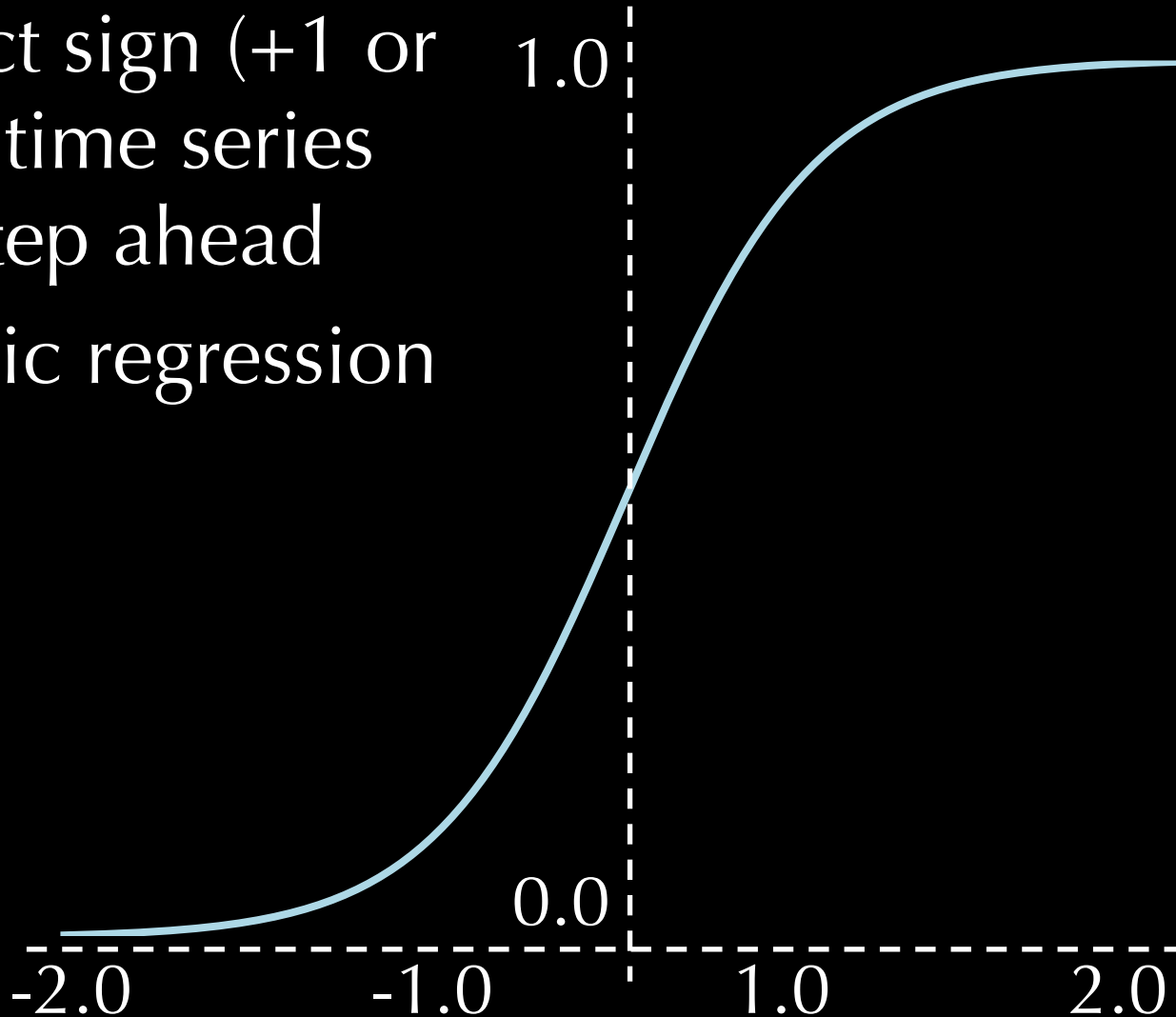
Making predictions

Making predictions

- Predict sign (+1 or -1) of time series one step ahead

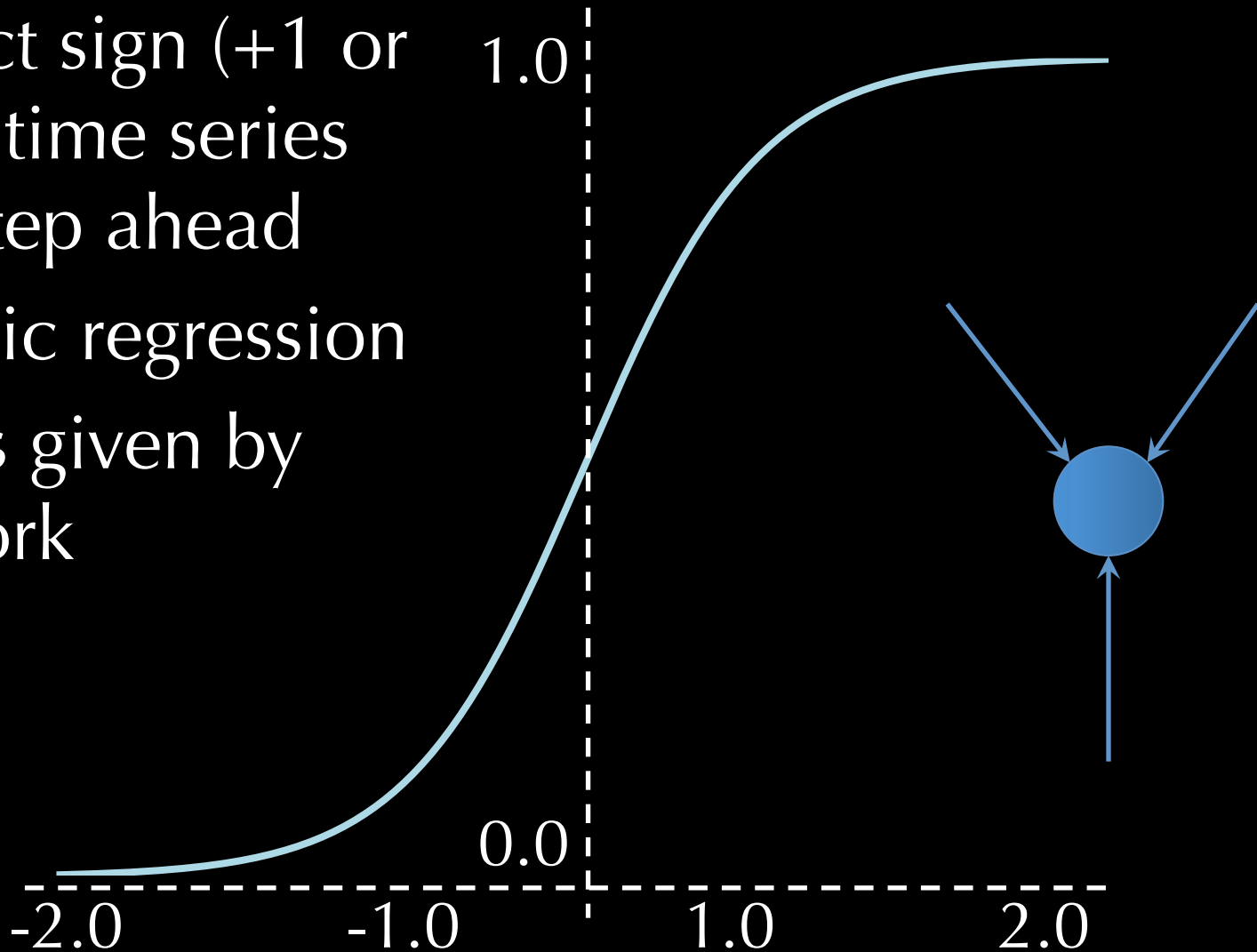
Making predictions

- Predict sign (+1 or -1) of time series one step ahead
- Logistic regression



Making predictions

- Predict sign (+1 or -1) of time series one step ahead
- Logistic regression
- Inputs given by network



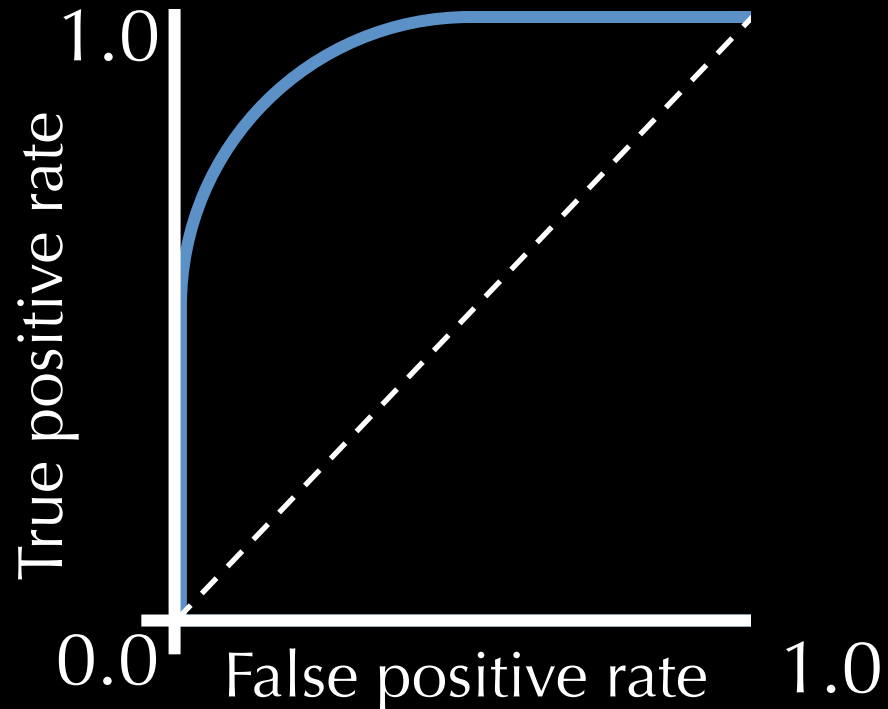
Evaluation

- Divide data into training and test sets.
- Construct network and train logistic regressions using training set.
- Evaluate accuracy on test set.

Evaluation

- Divide data into training and test sets.
- Construct network and train logistic regressions using training set.
- Evaluate accuracy on test set.

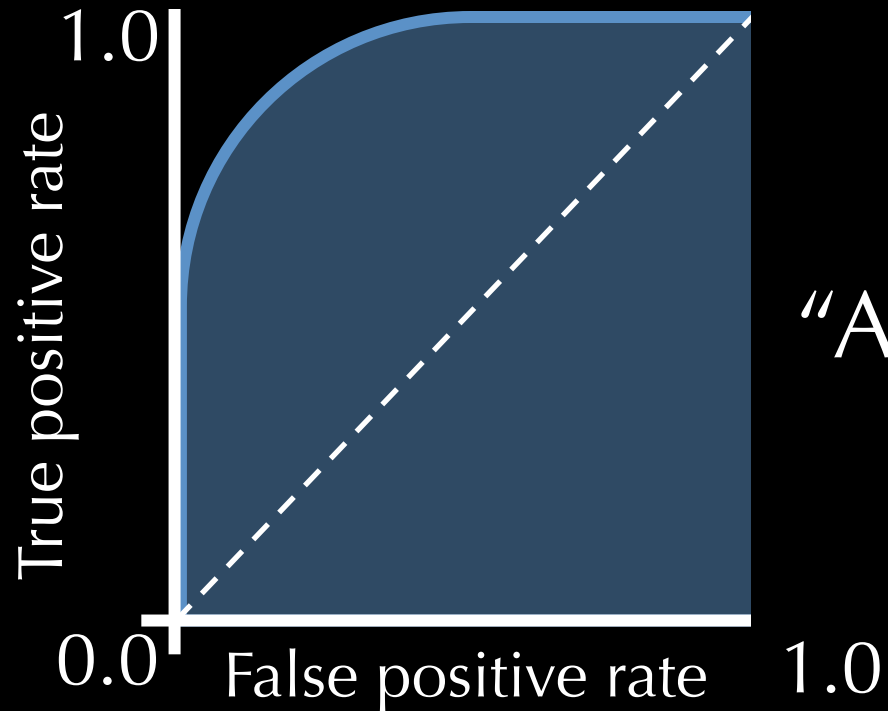
“ROC Curve”



Evaluation

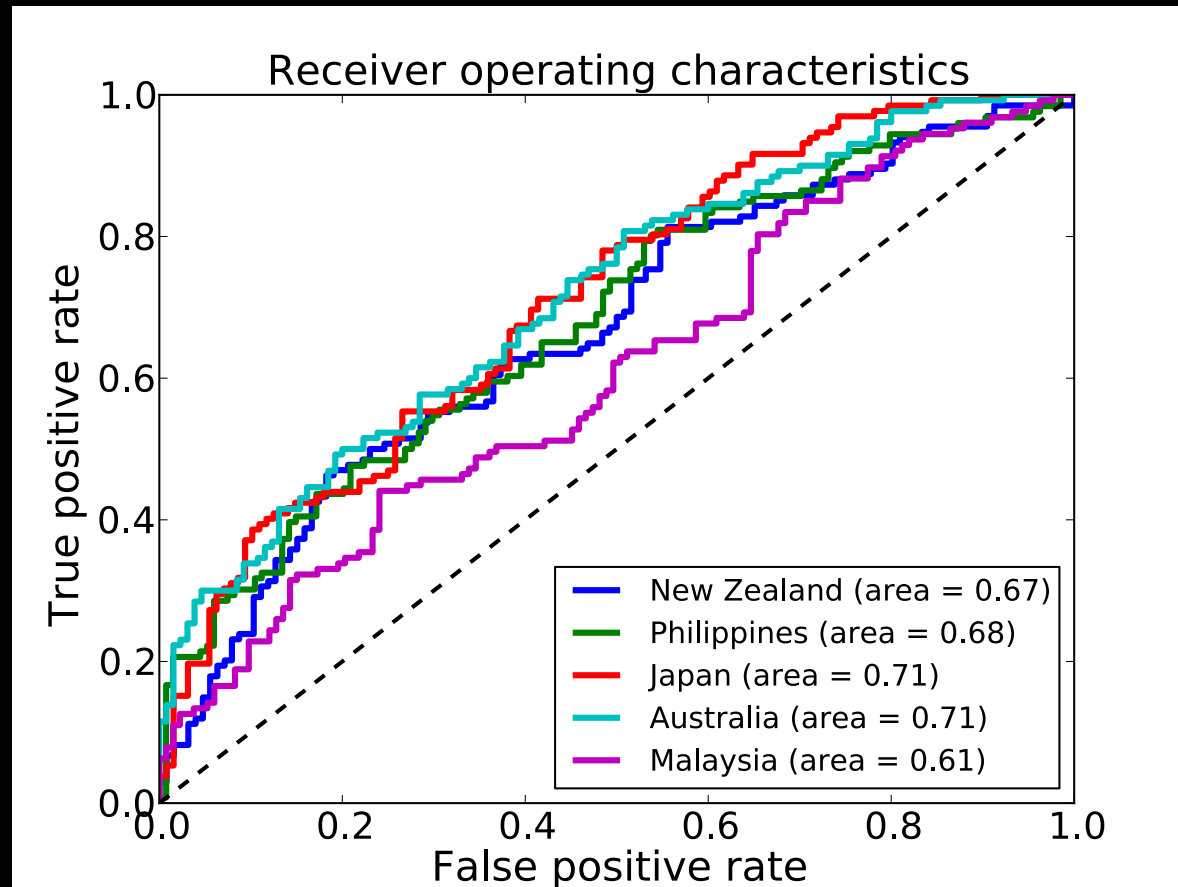
- Divide data into training and test sets.
- Construct network and train logistic regressions using training set.
- Evaluate accuracy on test set.

“ROC Curve”

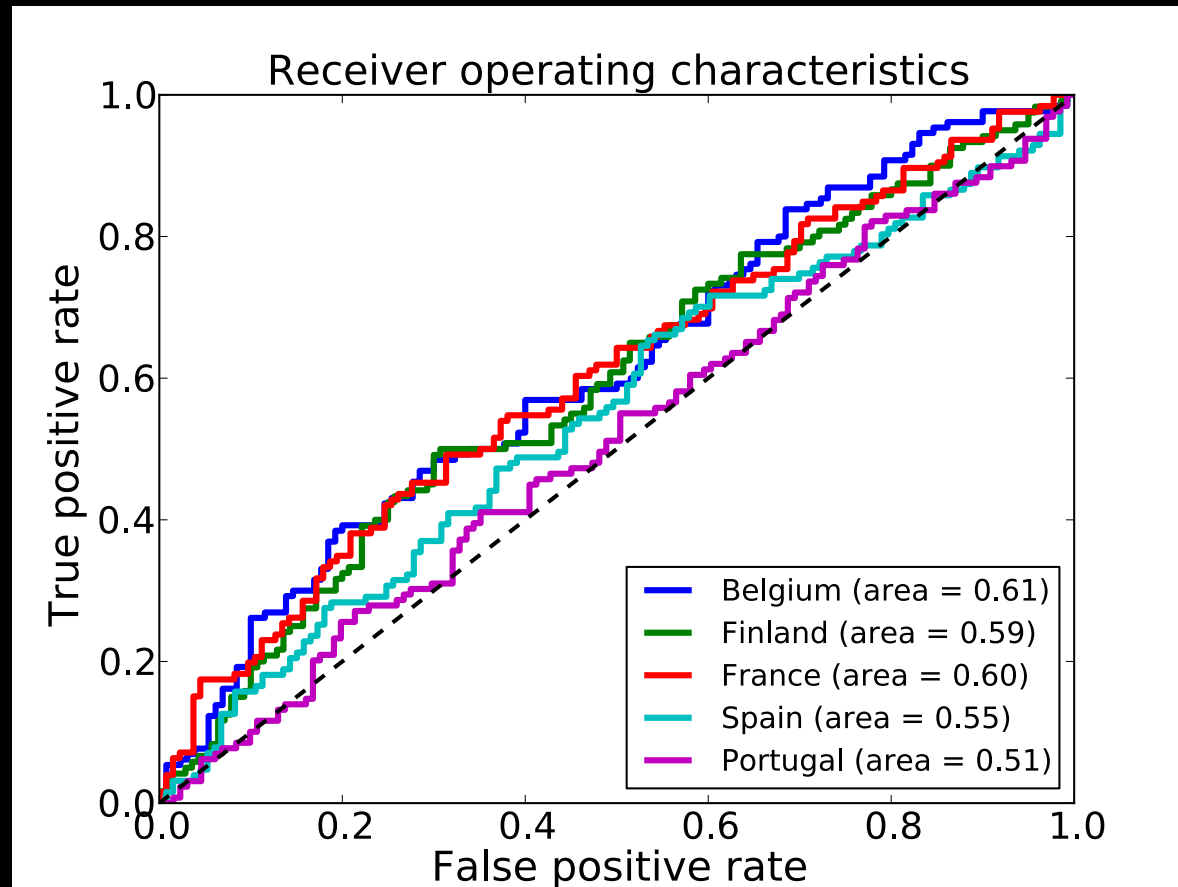


“AUC”

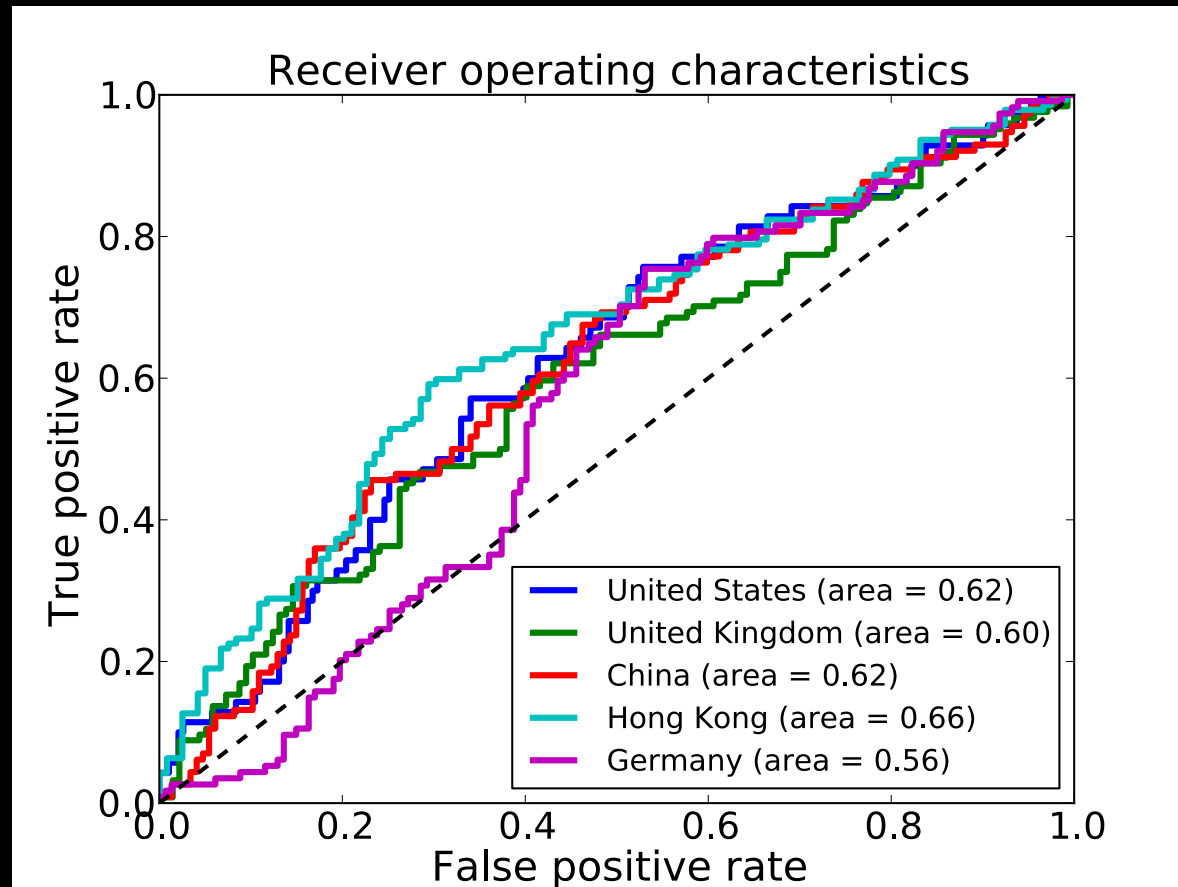
Network captures predictive relationships



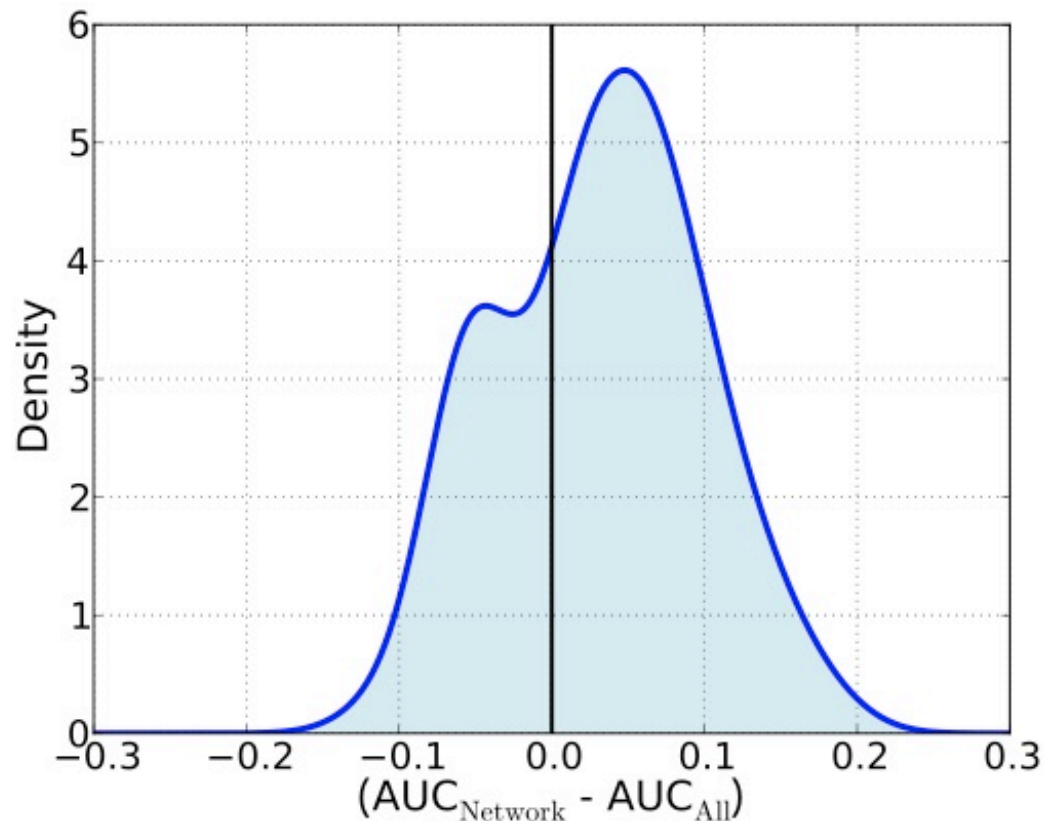
Network captures predictive relationships



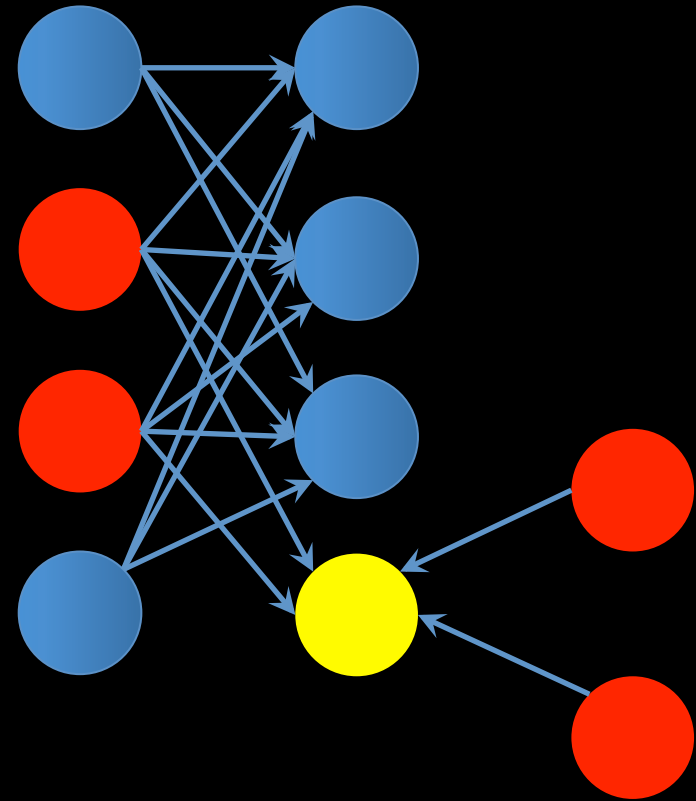
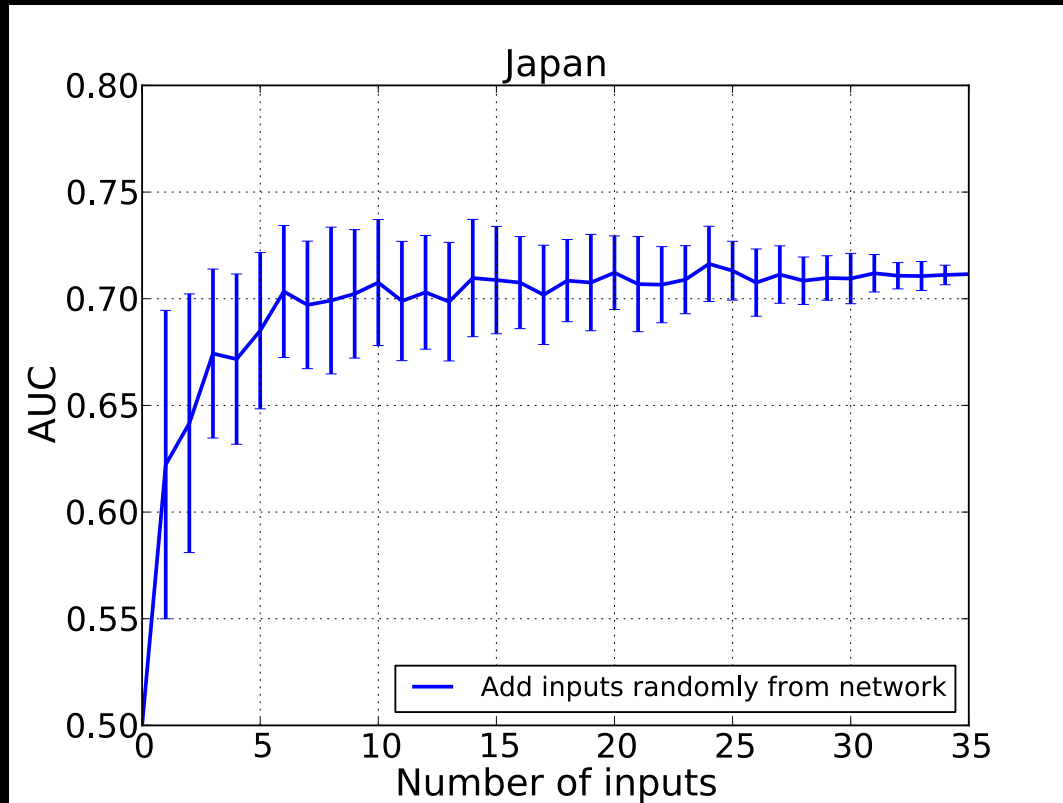
Network captures predictive relationships



Restricting to network inputs boosts accuracy

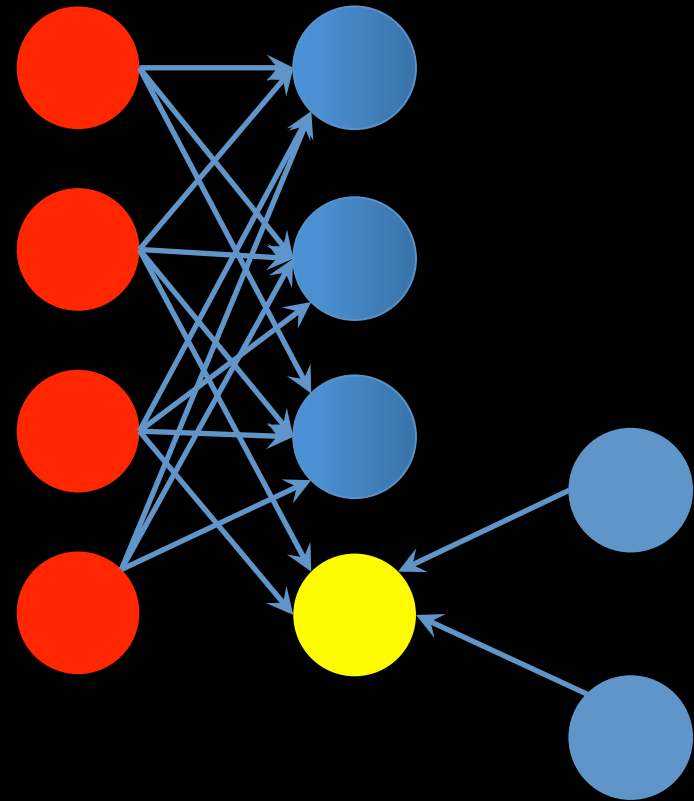
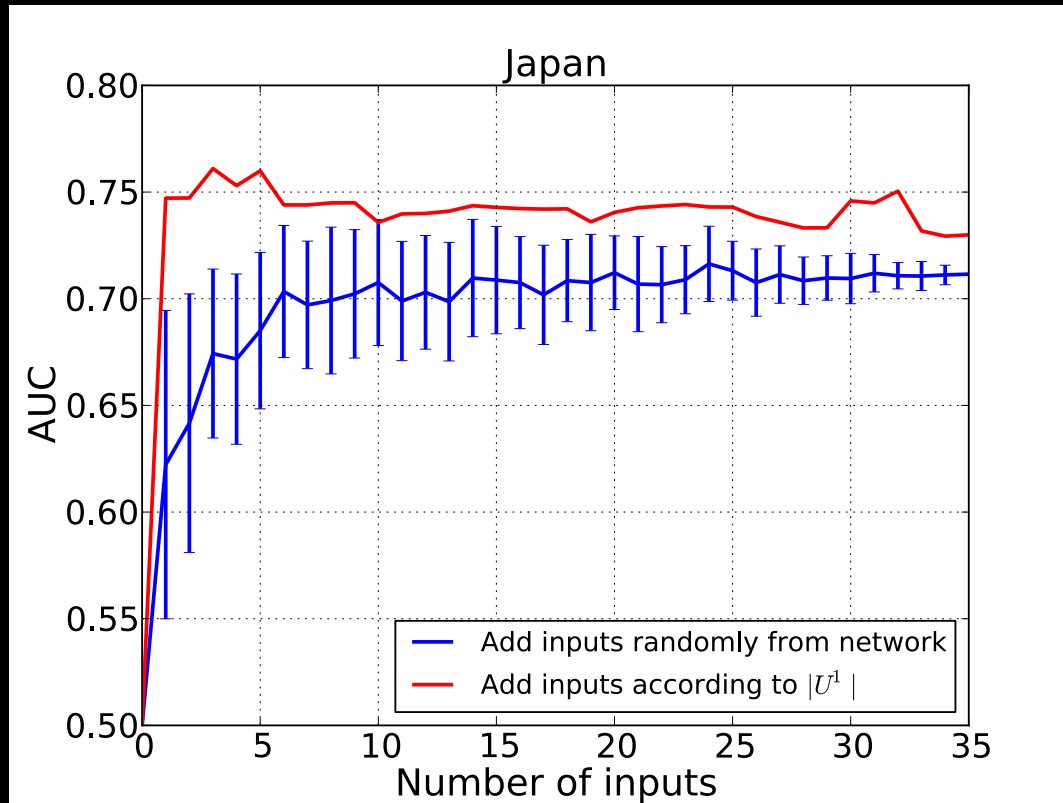


Using communities to recommend inputs



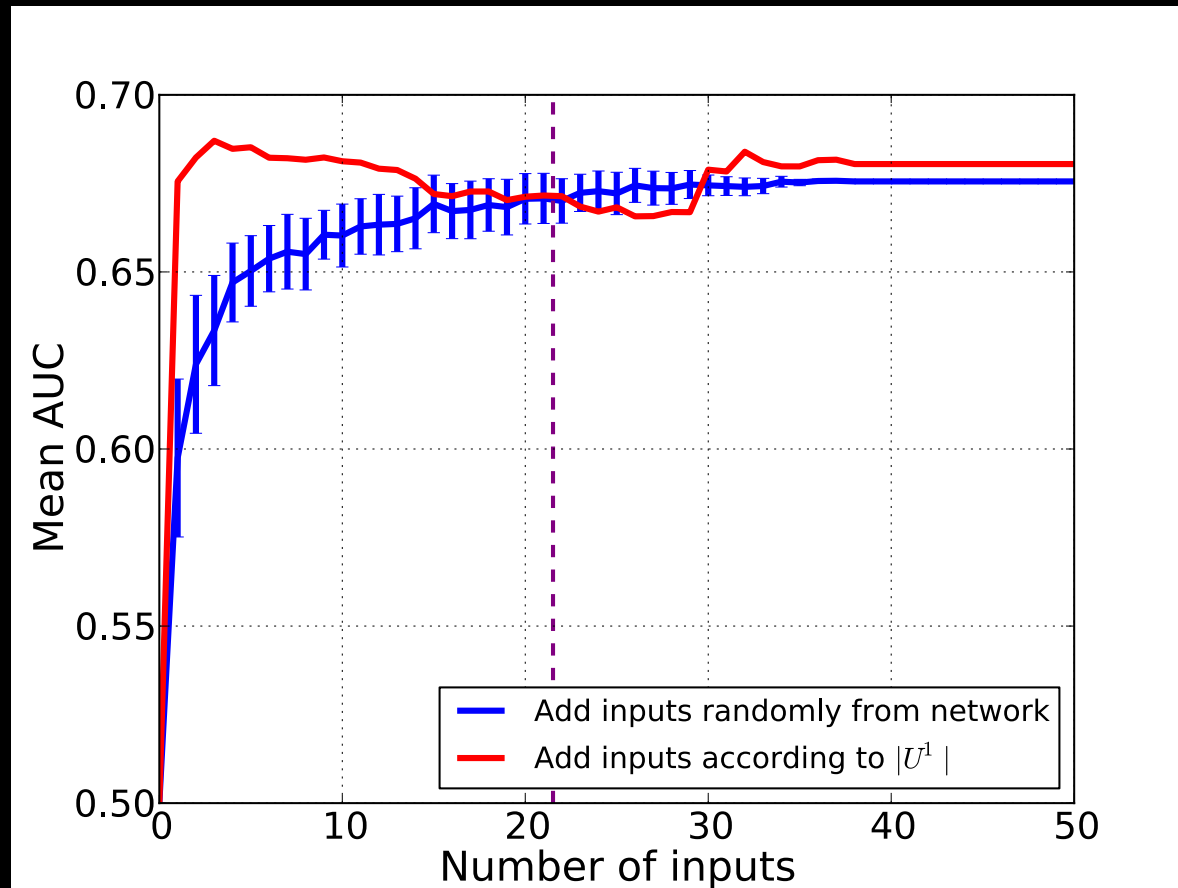
Element of V^1

Using communities to recommend inputs



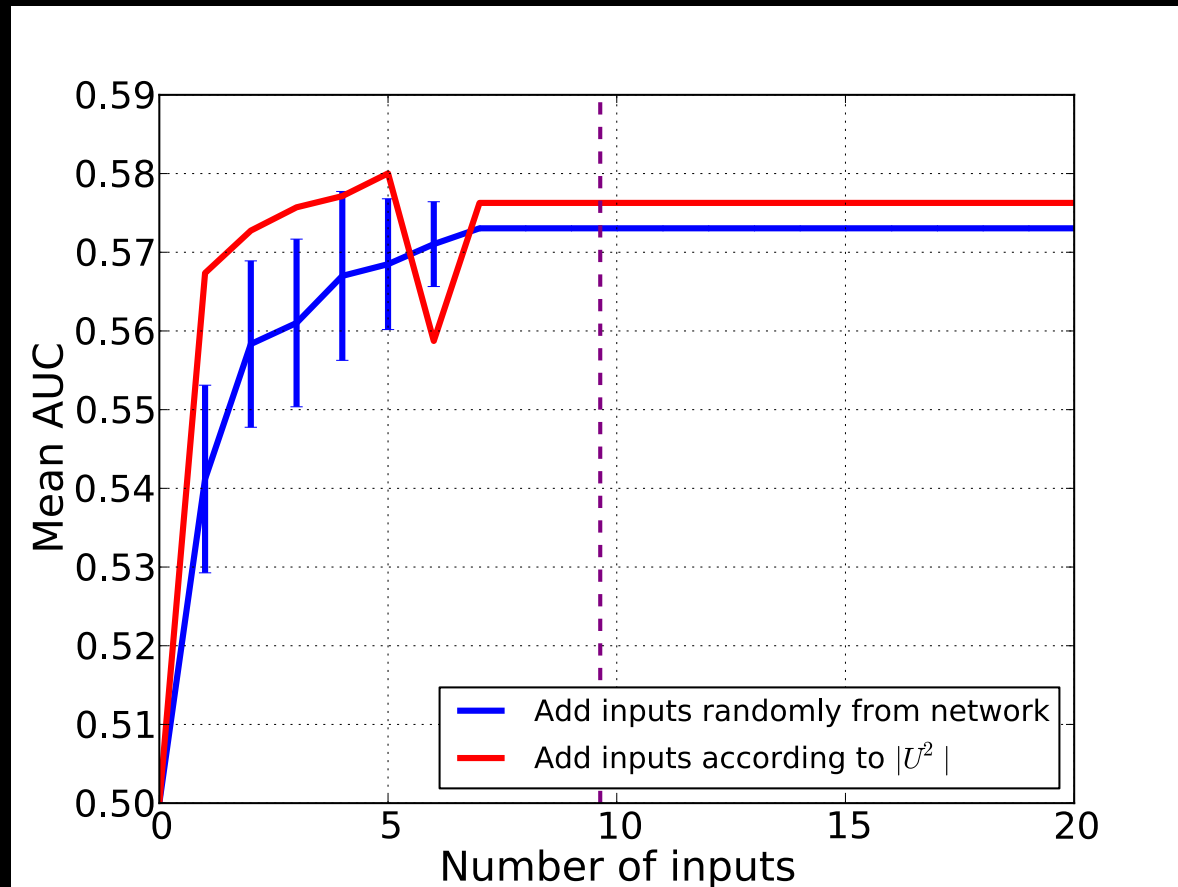
Element of V^1

Using communities to recommend inputs



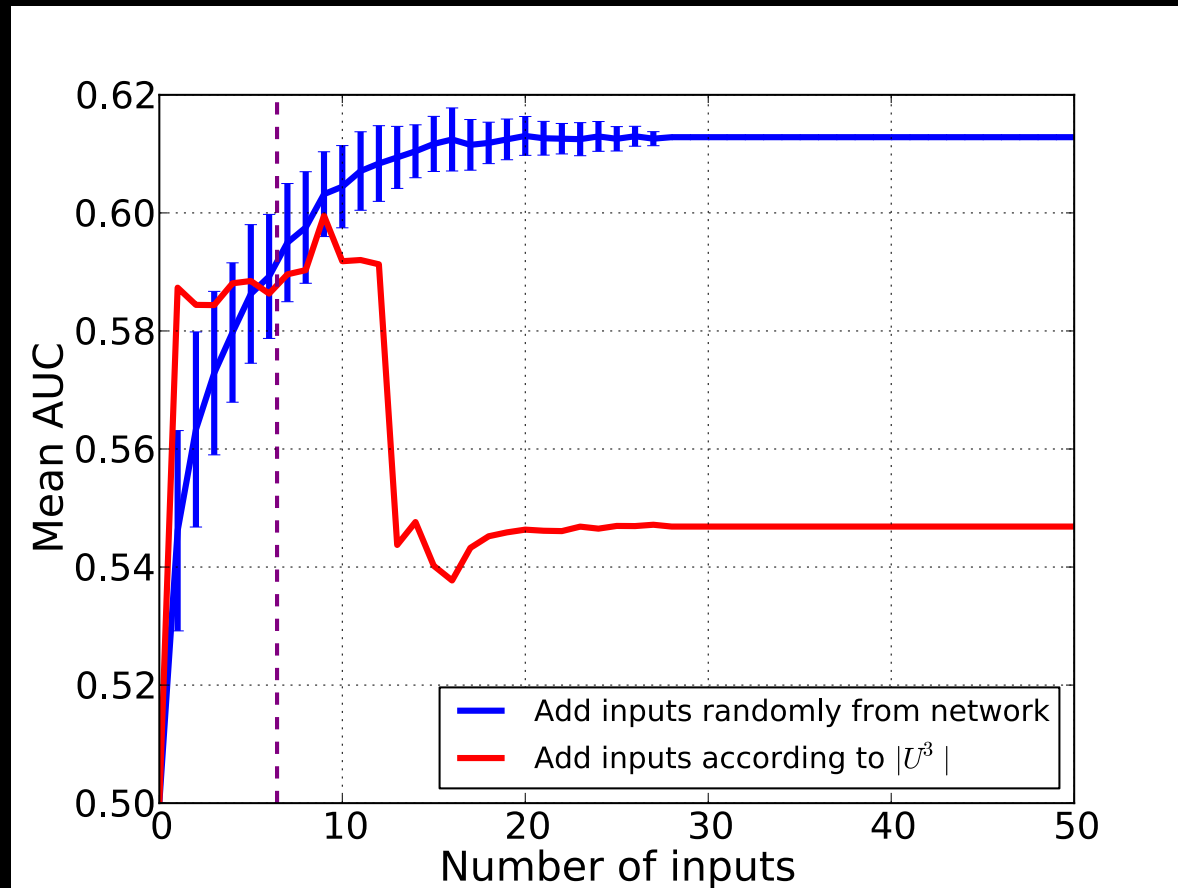
Elements of V^1

Using communities to recommend inputs



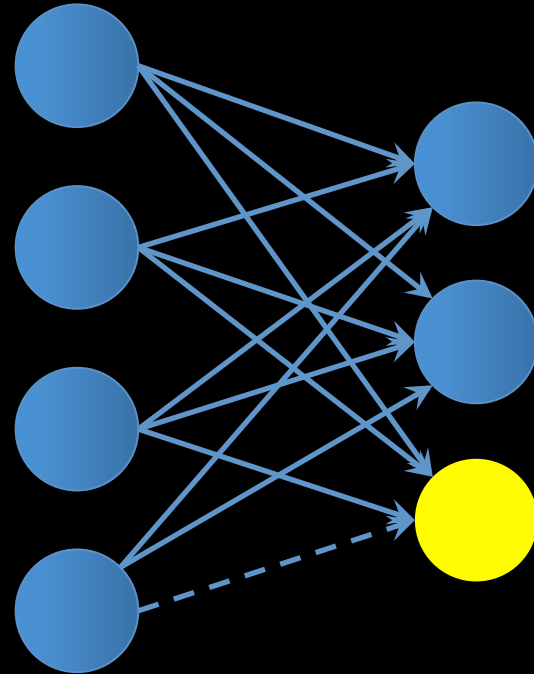
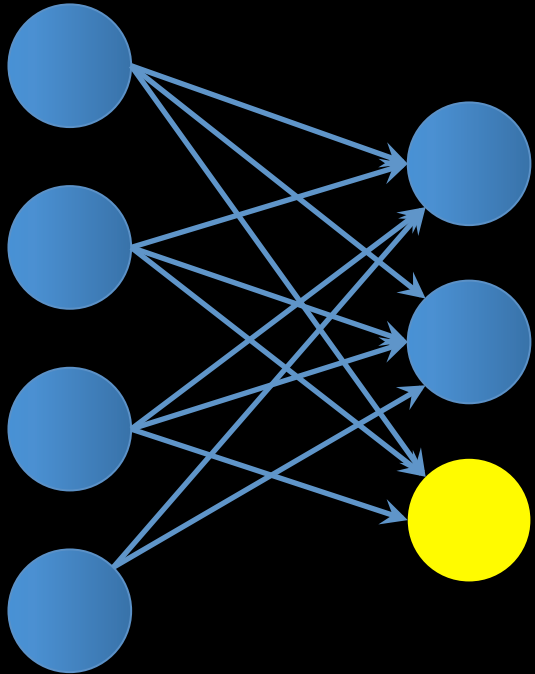
Elements of V^2

Using communities to recommend inputs



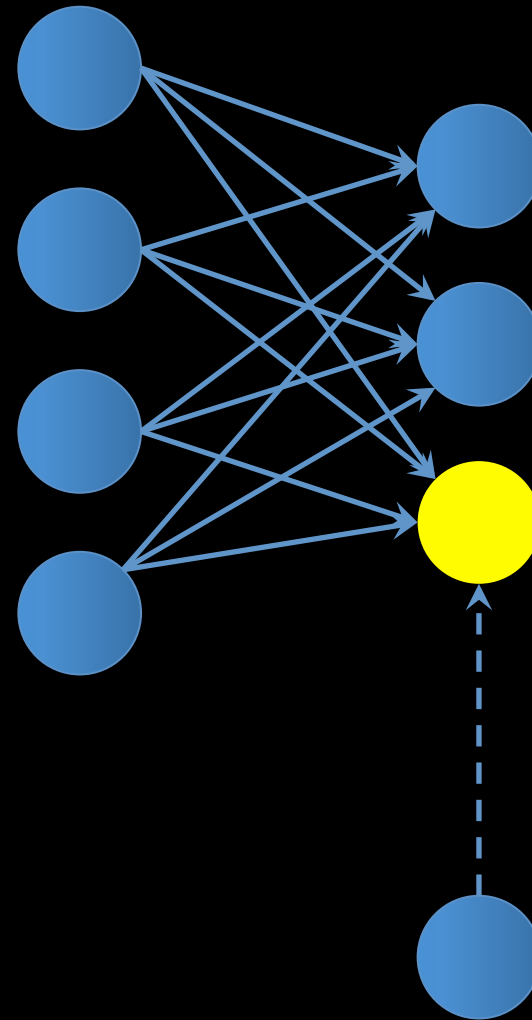
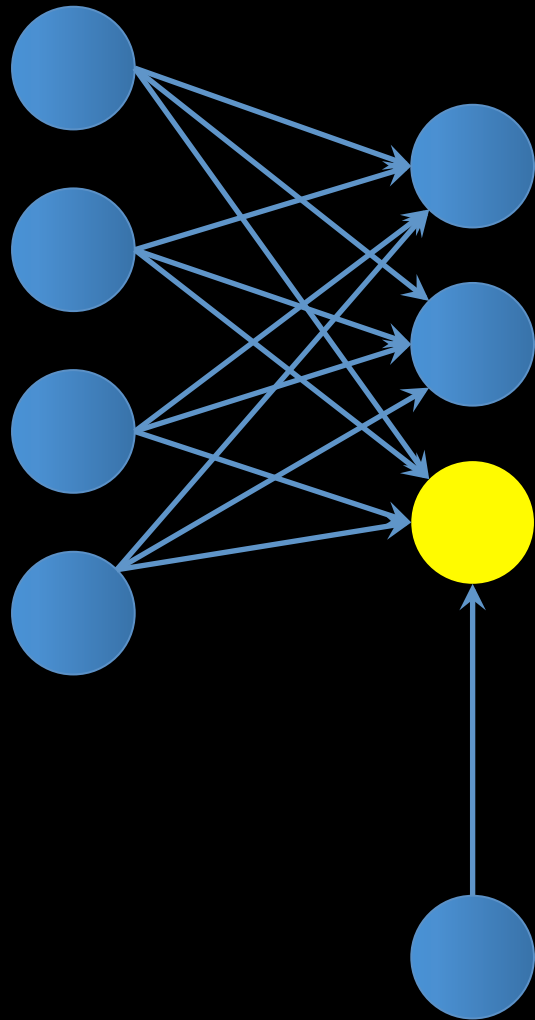
Elements of V^3

Recommender system interpretation



Bolster against missing links

Recommender system interpretation



...and spurious links.

Summary

- SVN methodology reveals global network of interactions among market movements and financial news sentiment signals.
 - News responds to market movements.

Summary

- SVN methodology reveals global network of interactions among market movements and financial news sentiment signals.
 - News responds to market movements.
- Community structures show collective interactions among groups of countries.

Summary

- SVN methodology reveals global network of interactions among market movements and financial news sentiment signals.
 - News responds to market movements.
- Community structures show collective interactions among groups of countries.
- In this setting, community structures simultaneously form the basis of a “recommender system” for model inputs.

Thank you!

Questions?