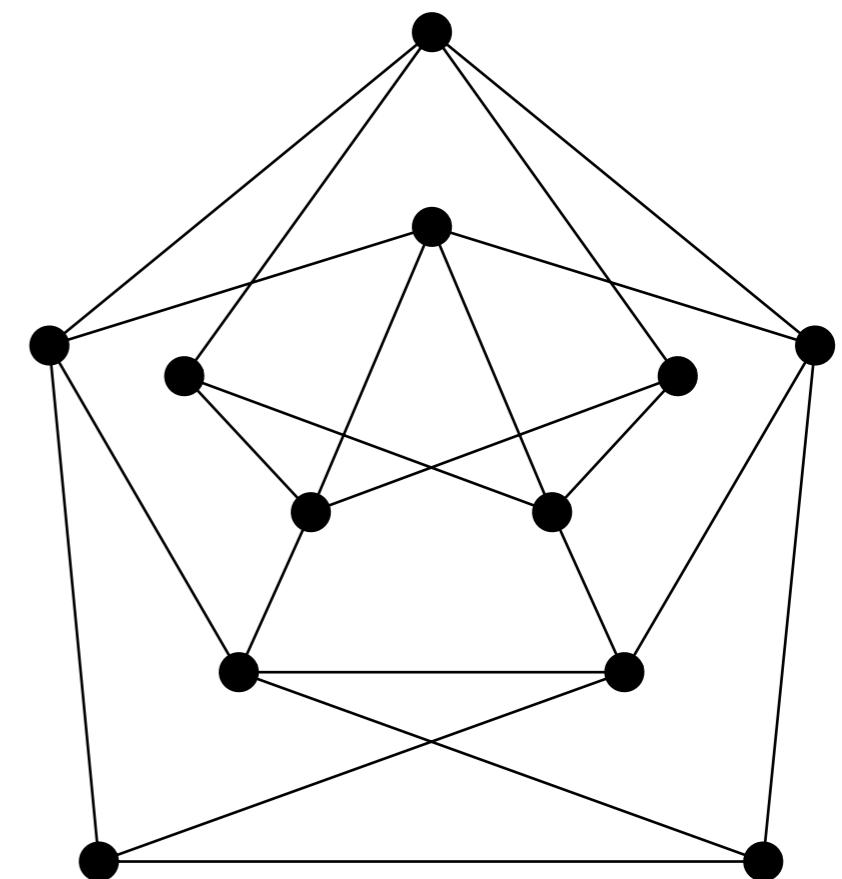


Cycles in Consensus Networks: Performance and Design

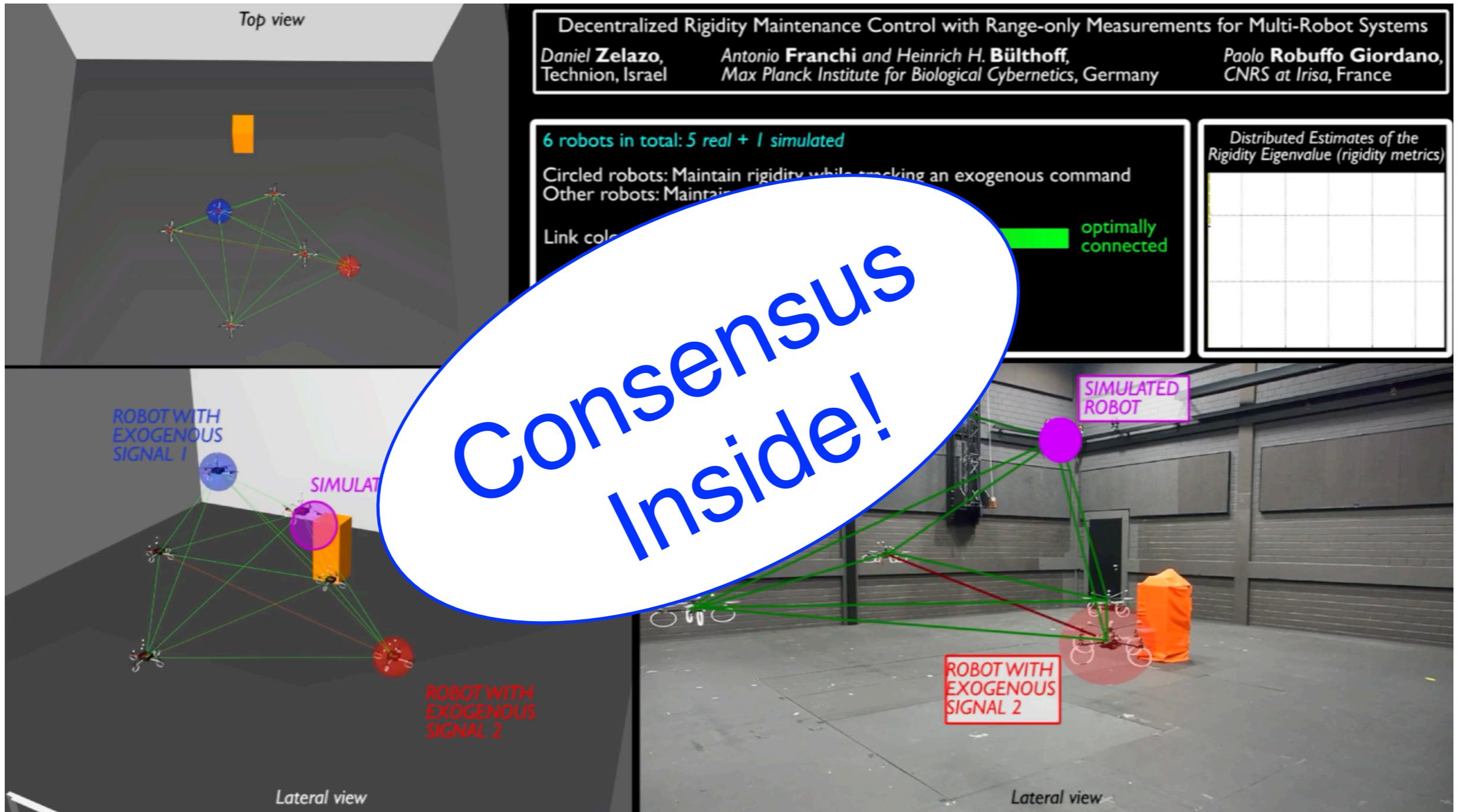
Daniel Zelazo

Faculty of Aerospace Engineering
Technion-Israel Institute of Technology

NCEPU September 2, 2013
Beijing, China



Networked Dynamic Systems



* this talk is not about robots...



הפקולטה להנדסת אירונוטיקה וחלל

Faculty of Aerospace Engineering

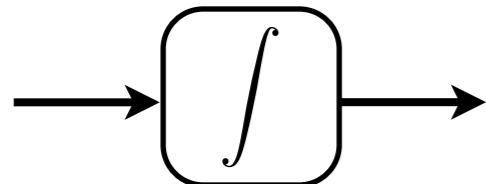
NCEPU September 2, 2013,
Beijing, China

The Consensus Protocol

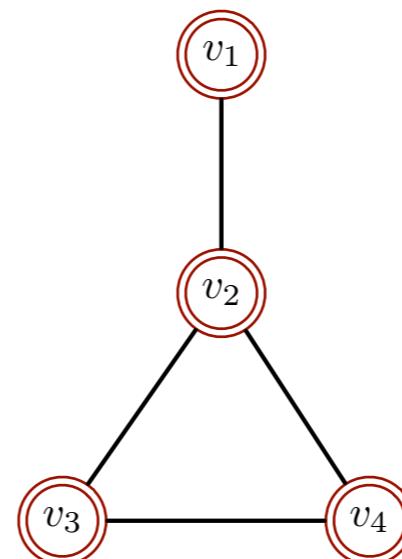
The consensus protocol is a *distributed and dynamic protocol* used for computing the average of a set of numbers.

Agent Dynamics

$$\dot{x}_i(t) = u_i(t)$$



Information Exchange Network



$$\mathcal{G} = (\mathcal{V}, \mathcal{E})$$

Incidence Matrix

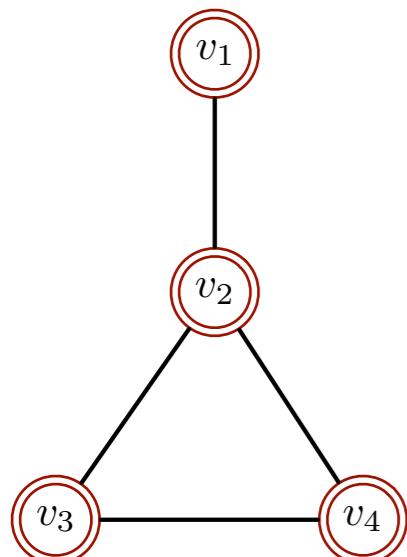
$$E(\mathcal{G}) \in \mathbb{R}^{|\mathcal{V}| \times |\mathcal{E}|}$$

$$E(\mathcal{G}) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ -1 & 1 & -1 & 0 \\ 0 & -1 & 0 & 1 \\ 0 & 0 & 1 & -1 \end{bmatrix}$$



The Consensus Protocol

The consensus protocol is a *distributed and dynamic protocol* used for computing the average of a set of numbers.



Consensus Protocol

$$u_i(t) = \sum_{i \sim j} (x_j(t) - x_i(t))$$

$$\dot{x}(t) = -L(\mathcal{G})x(t)$$

Laplacian Matrix

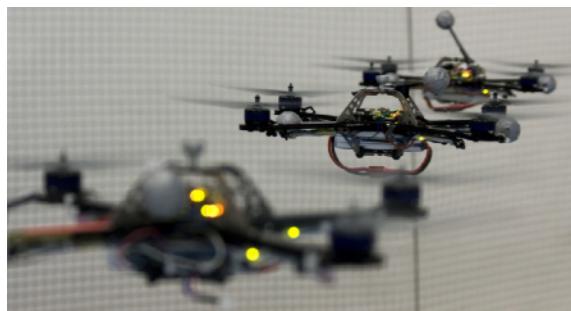
- $L(\mathcal{G}) \in \mathbb{R}^{|\mathcal{V}| \times |\mathcal{V}|}$
- $L(\mathcal{G}) = E(\mathcal{G})E(\mathcal{G})^T$
- $L(\mathcal{G})\mathbf{1} = 0$

$$\lim_{t \rightarrow \infty} x(t) = \left(\frac{\mathbf{1}^T x(0)}{|\mathcal{V}|} \right) \mathbf{1}$$

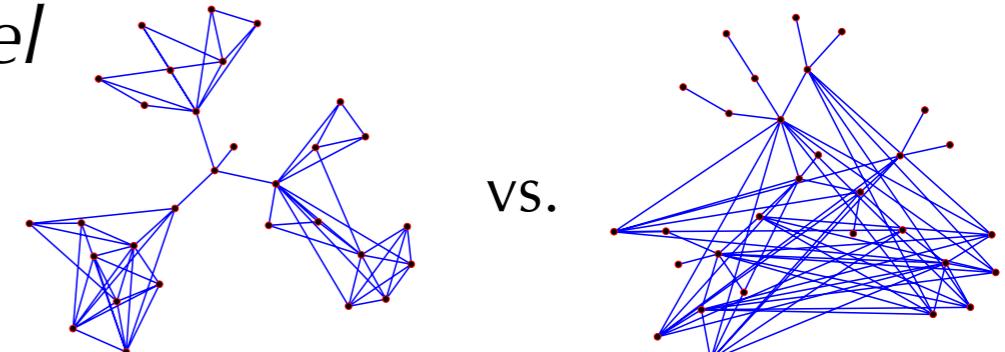


Consensus-Seeking Networks

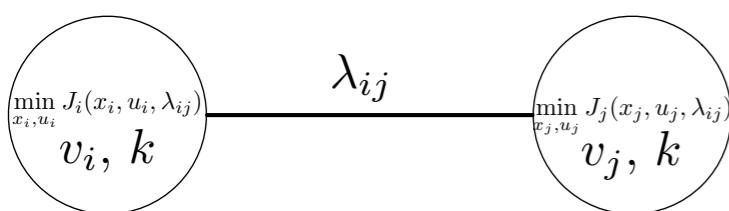
The consensus protocol is a *canonical model* for studying complex networked systems



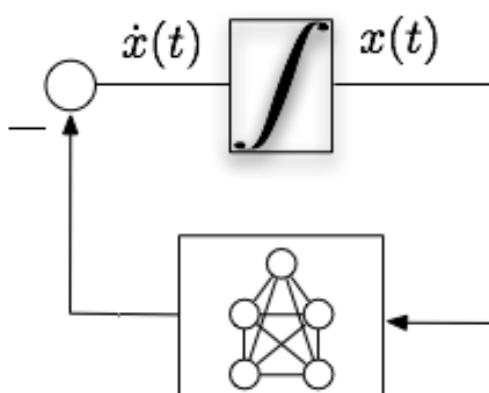
formation
control



Are certain information structures more favorable to others?



distributed
optimization



systems theory
over graphs

$$\begin{matrix} \mathcal{H}_2 \\ \mathcal{H}_\infty \\ \vdots \end{matrix} \propto \begin{matrix} \text{cycle lengths} \\ \text{node degree} \\ \vdots \end{matrix}$$

Can notions of *dynamic system performance* be explained in terms of *properties of the graph*?

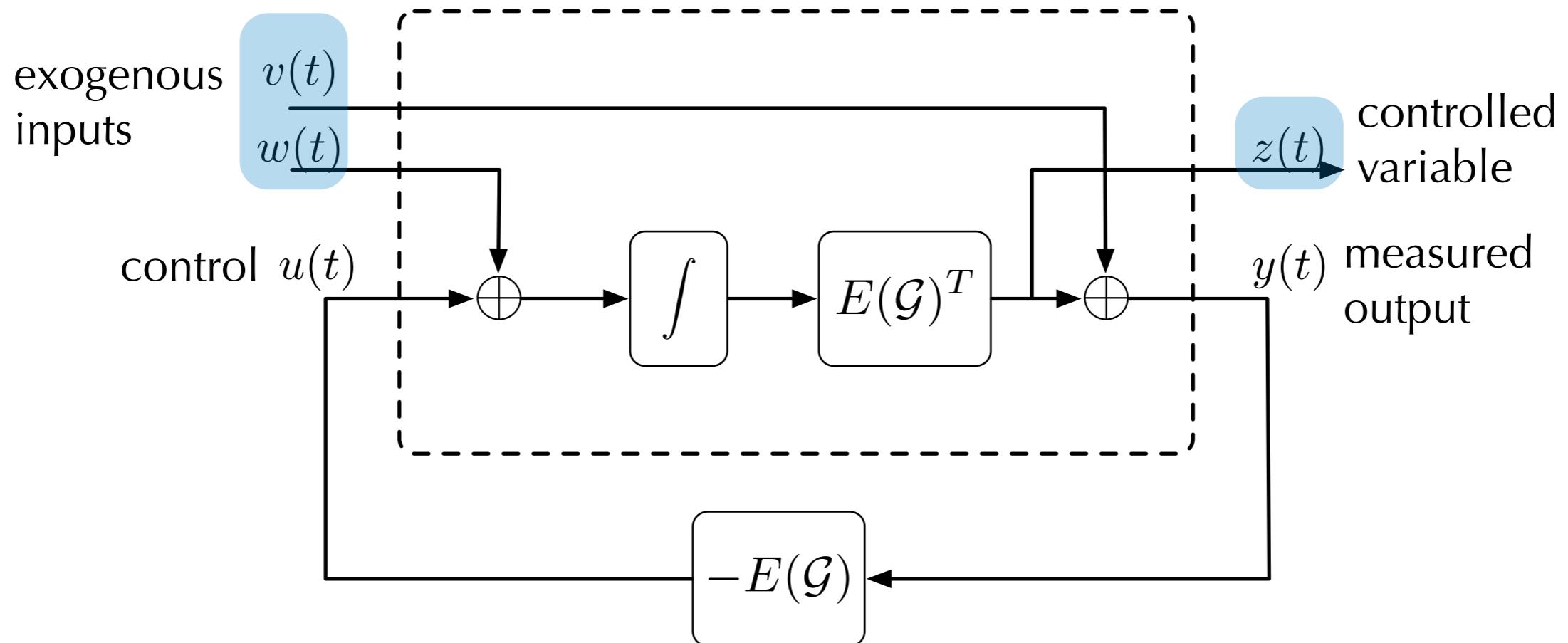
$$\min_{\mathcal{G}} \|\Sigma(\mathcal{G})\|_p$$

How do we *synthesize* good information structures?



A Two-Port Consensus System

An 'input-output' consensus model

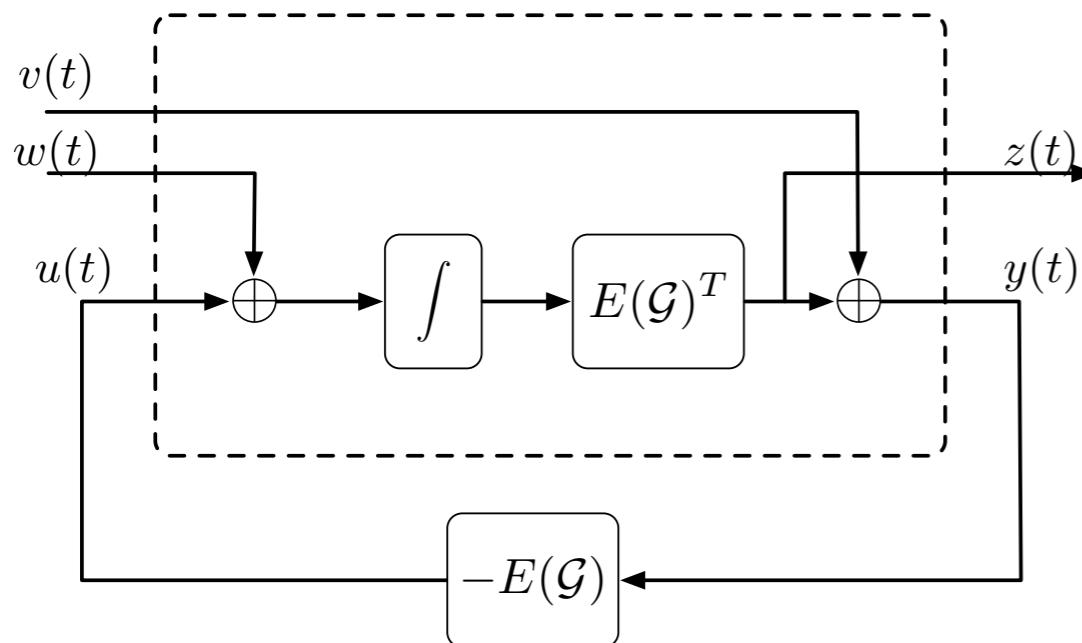


How do disturbances and noises affect the performance of the consensus protocol?

\mathcal{H}_2



A Two-Port Consensus System



$$\Sigma(\mathcal{G}) : \begin{cases} \dot{x}(t) &= -\textcolor{brown}{L}(\mathcal{G})x(t) + \begin{bmatrix} I & -E(\mathcal{G}) \end{bmatrix} \begin{bmatrix} w(t) \\ v(t) \end{bmatrix} \\ z(t) &= E(\mathcal{G})^T x(t). \end{cases}$$

recall...

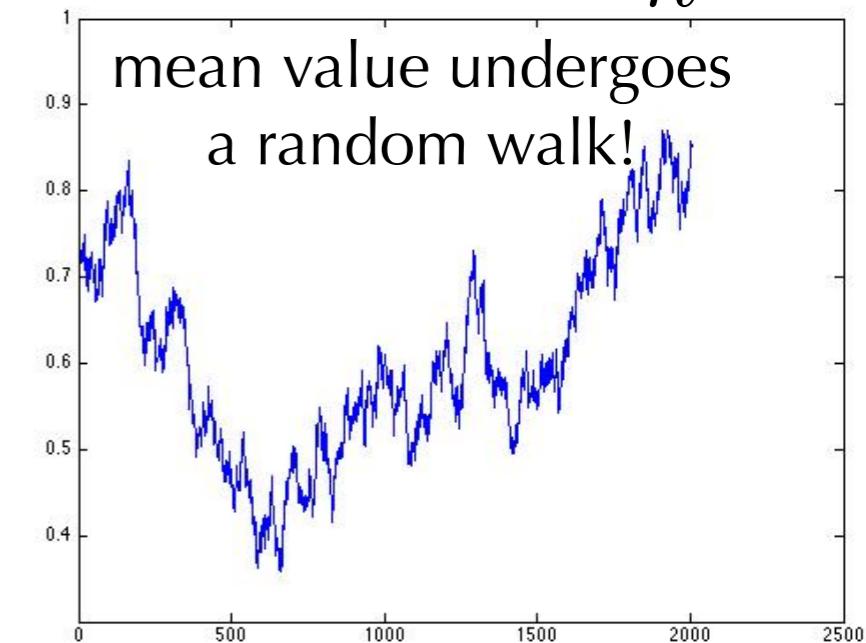
The \mathcal{H}_2 performance of a linear system characterizes how a WGN exogenous input propagates through the system and effects the variance of the output.

$\|\Sigma(\mathcal{G})\|_2$ is unbounded!

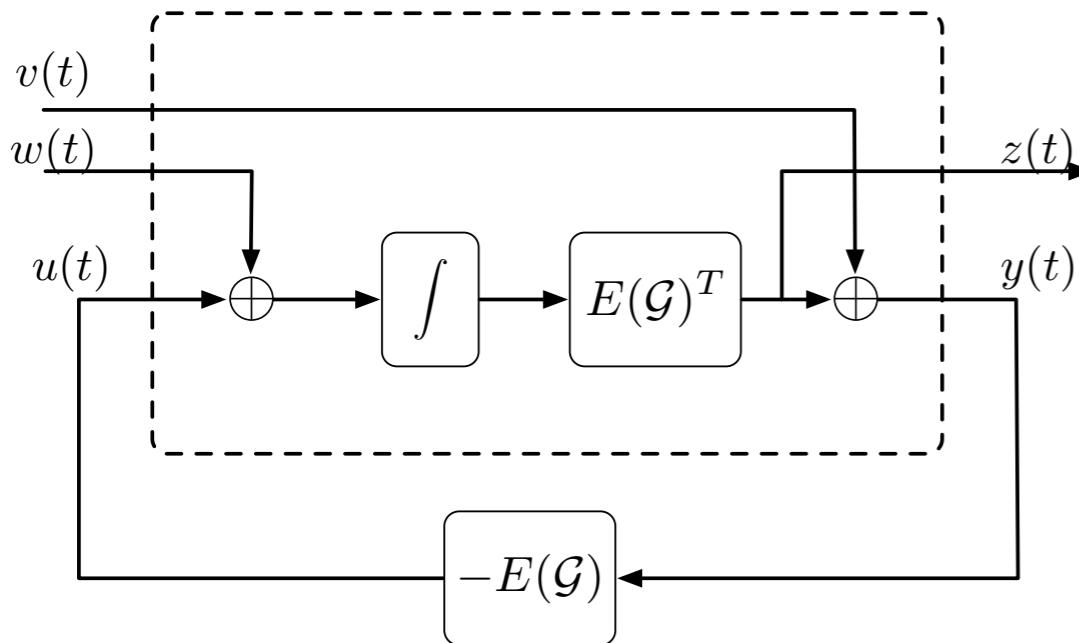
$$\bar{x}(t) = \frac{1}{n} \mathbf{1}^T x(t)$$

$$\dot{\bar{x}}(t) = \frac{1}{n} \mathbf{1}^T \dot{x}(t)$$

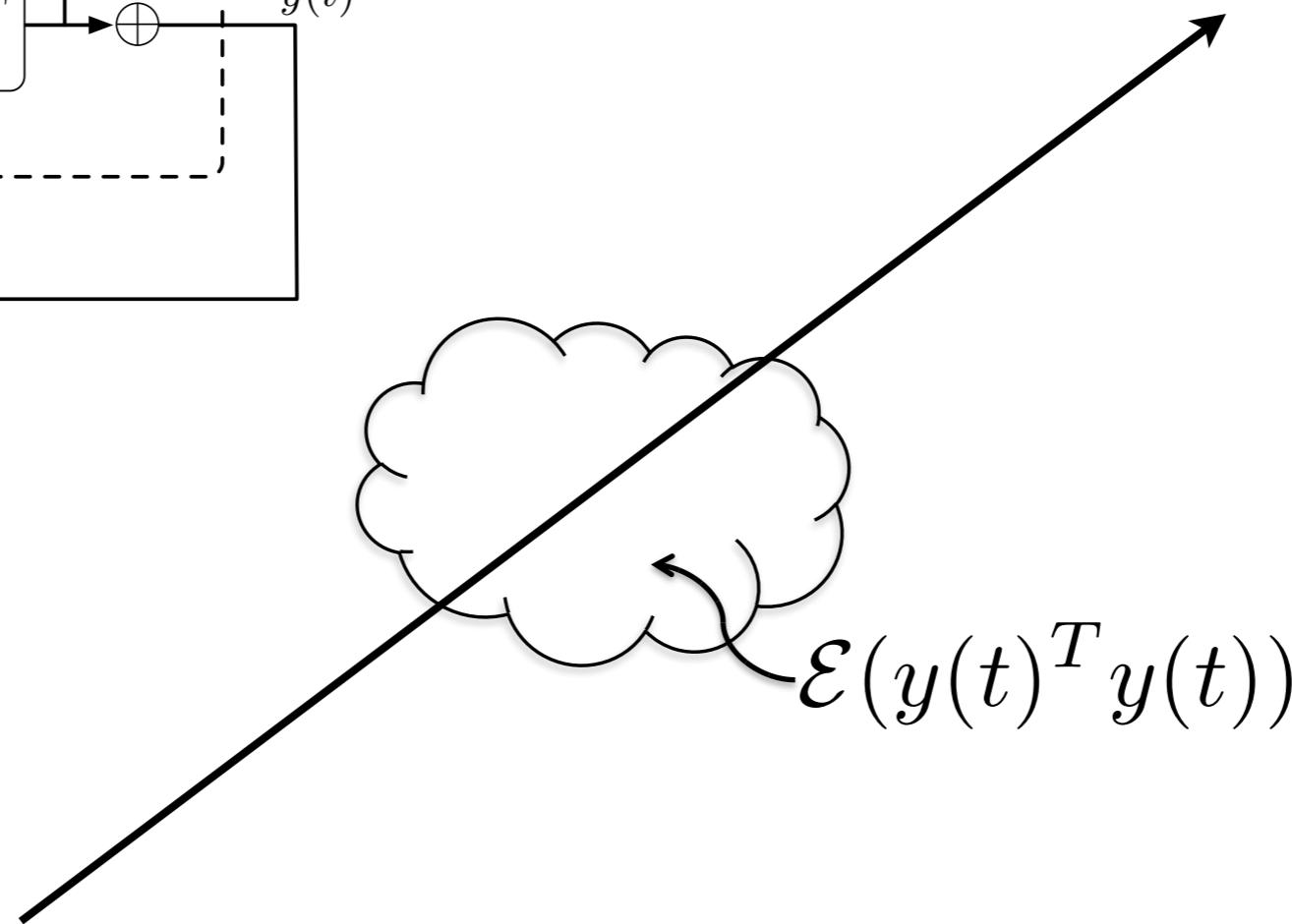
$$\mathcal{E}(\bar{x}(t)^2) = \frac{\sigma_w^2}{n} t$$



Performance Interpretations



$$\mathcal{N}(E(\mathcal{G})^T) = \text{span}\{1\}$$



When driven by noise, it is meaningful to examine how noises effect the steady-state covariance of the *relative states*

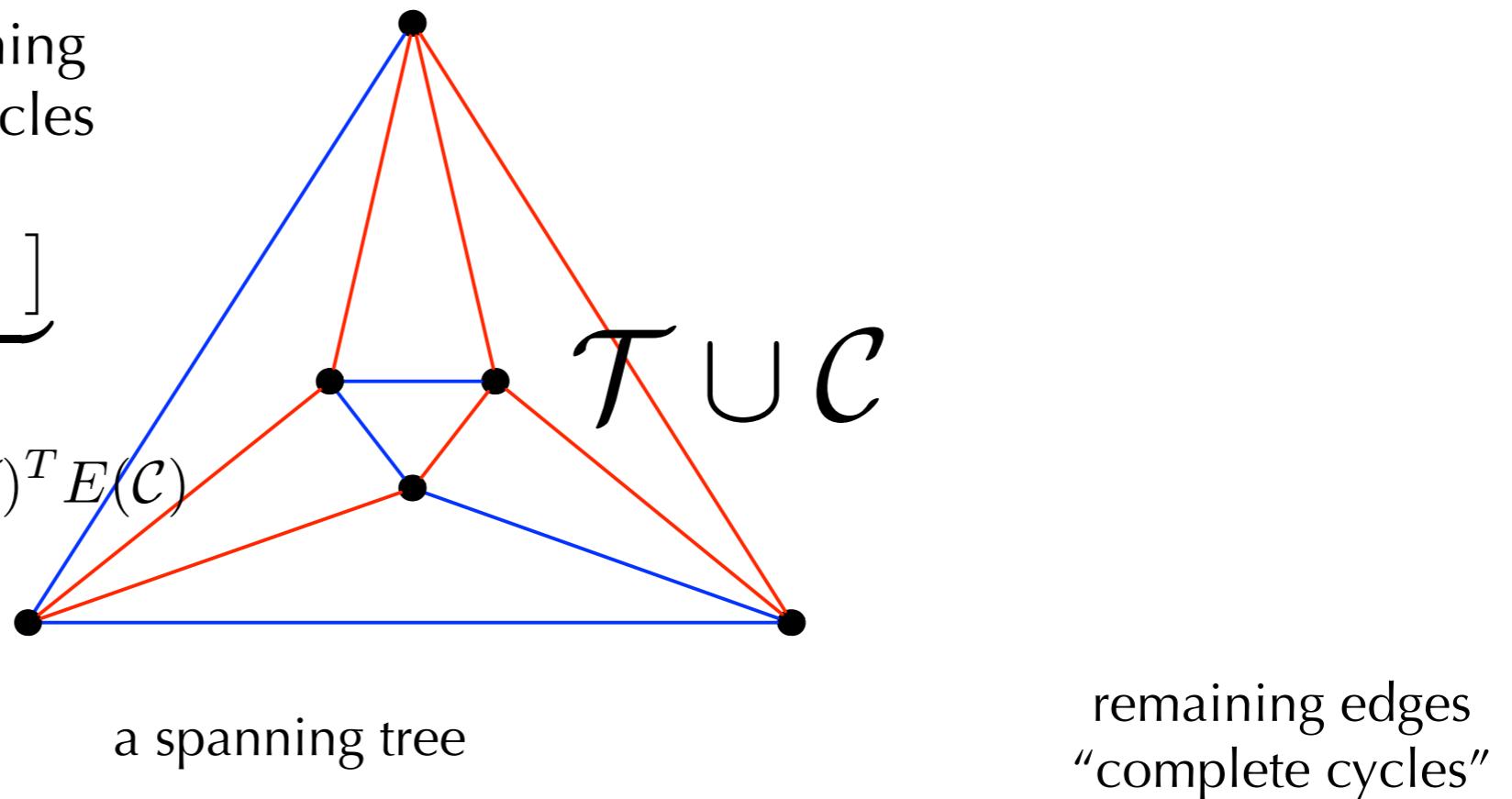


Spanning Trees and Cycles

A graph as the union of a spanning tree and edges that complete cycles

$$E(\mathcal{G}) = E(\mathcal{T}) \underbrace{\begin{bmatrix} I & T_{(\mathcal{T},\mathcal{C})} \end{bmatrix}}_{\mathcal{R}_{(\mathcal{T},\mathcal{C})}}$$

$$T_{(\mathcal{T},\mathcal{C})} = (E(\mathcal{T})^T E(\mathcal{T}))^{-1} E(\mathcal{T})^T E(\mathcal{C})$$



Edge Laplacian

$$L_e(\mathcal{G}) = E(\mathcal{G})^T E(\mathcal{G})$$

$\mathcal{R}_{(\mathcal{T},\mathcal{C})}$ rows form a basis for the
cut space of the graph

Essential Edge Laplacian

$$L_e(\mathcal{T}) \mathcal{R}_{(\mathcal{T},\mathcal{C})} \mathcal{R}_{(\mathcal{T},\mathcal{C})}^T$$

similarity between edge
and graph Laplacians

$$L(\mathcal{G})$$

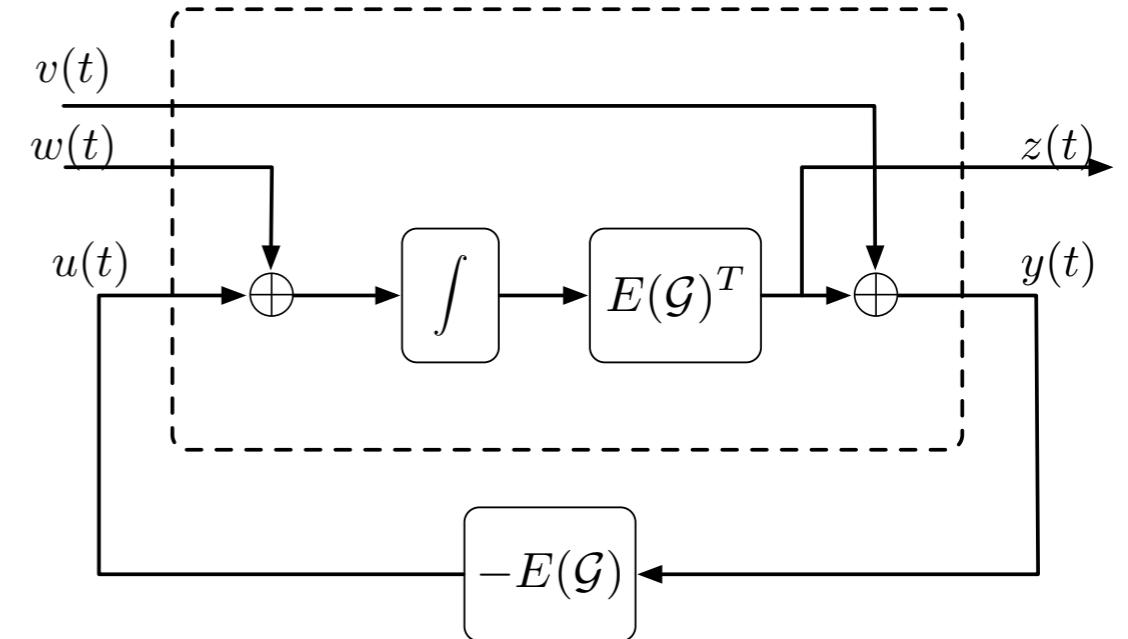
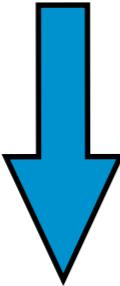
$$L_e(\mathcal{G})$$



The Edge Agreement Problem

$$\Sigma(\mathcal{G}) : \begin{cases} \dot{x}(t) = -L(\mathcal{G})x(t) + [I \quad -E(\mathcal{G})] \begin{bmatrix} w(t) \\ v(t) \end{bmatrix} \\ z(t) = E(\mathcal{G})^T x(t). \end{cases}$$

$$x_e(t) = \begin{bmatrix} E(\mathcal{T})^T \\ \frac{1}{n}\mathbf{1}^T \end{bmatrix} x(t)$$

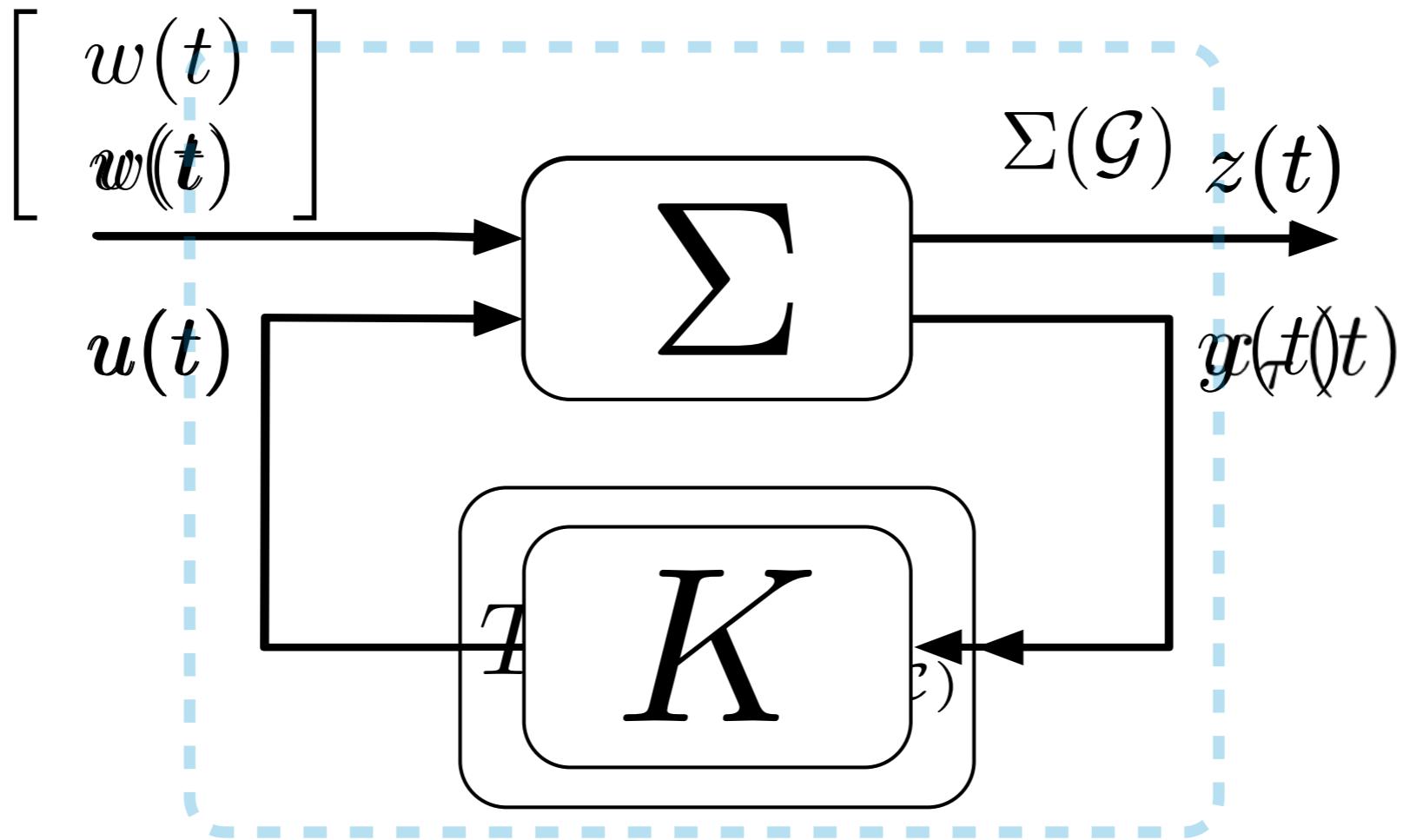


$$\Sigma_e(\mathcal{G}) : \begin{cases} \dot{x}_\tau(t) = -L_e(\mathcal{T})R_{(\tau,c)}R_{(\tau,c)}^T x_\tau(t) + [E(\mathcal{T})^T \quad -L_e(\mathcal{T})R_{(\tau,c)}] \begin{bmatrix} w(t) \\ v(t) \end{bmatrix} \\ z(t) = x_\tau(t). \end{cases}$$

stable and minimal
realization of
consensus protocol



Cycles as Feedback



$$R_{(\mathcal{T}, \mathcal{C})} = [I \quad T_{(\mathcal{T}, \mathcal{C})}]$$

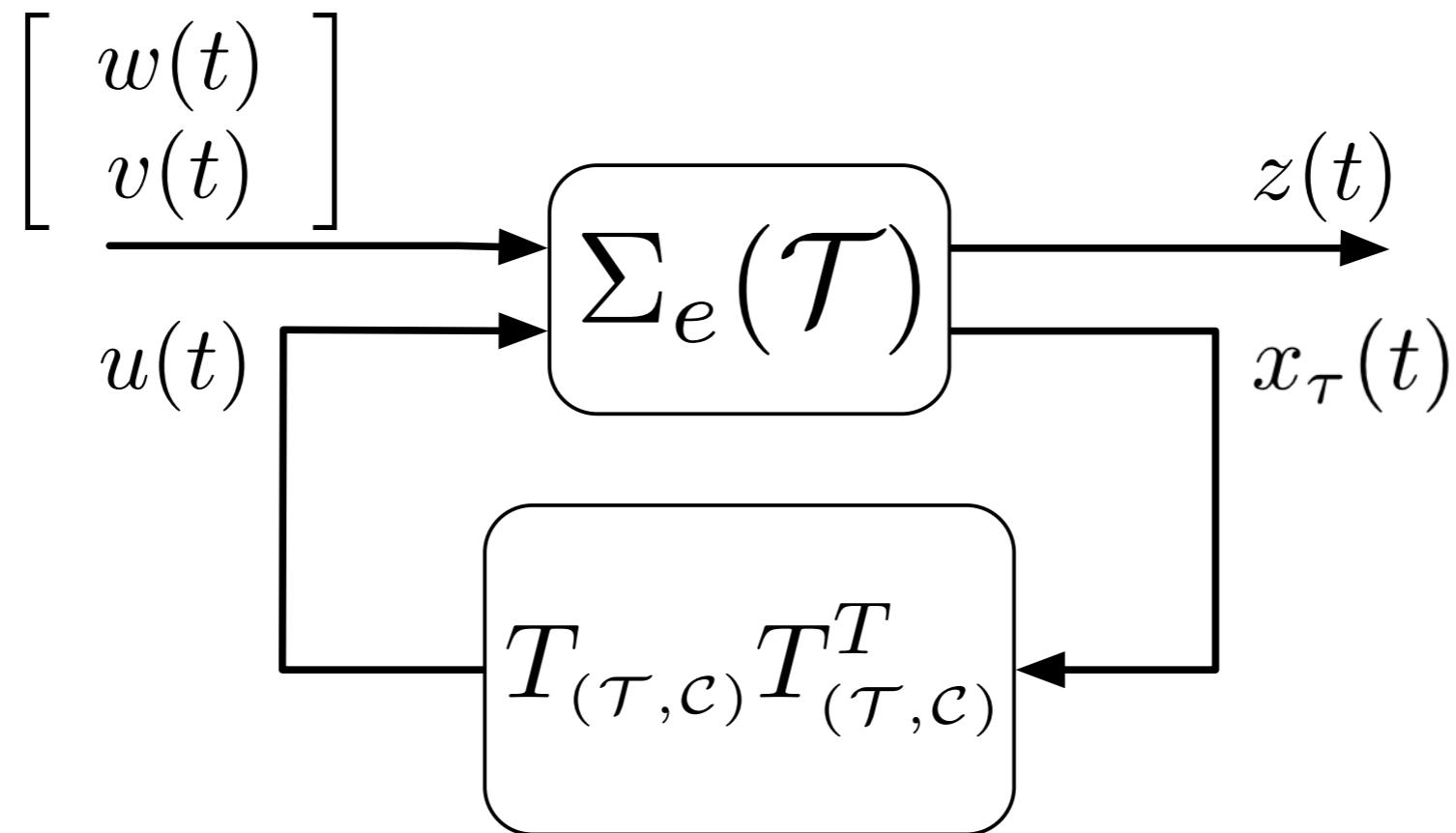
$$E(\mathcal{T})T_{(\mathcal{T}, \mathcal{C})} = E(\mathcal{C})$$

Design of consensus networks can be viewed as a state-feedback problem

$$L_e(\mathcal{T})R_{(\mathcal{T}, \mathcal{C})}R_{(\mathcal{T}, \mathcal{C})}^T = L_e(\mathcal{T}) + L_e(\mathcal{T})\underline{T_{(\mathcal{T}, \mathcal{C})}T_{(\mathcal{T}, \mathcal{C})}^T}$$



Cycles as Feedback



A synthesis problem

$$\min_{T_{(\tau,c)} \in \mathbb{R}^{|\mathcal{V}| \times k}} \|\Sigma_e(\mathcal{G})\|_2,$$



Performance of Consensus

Theorem

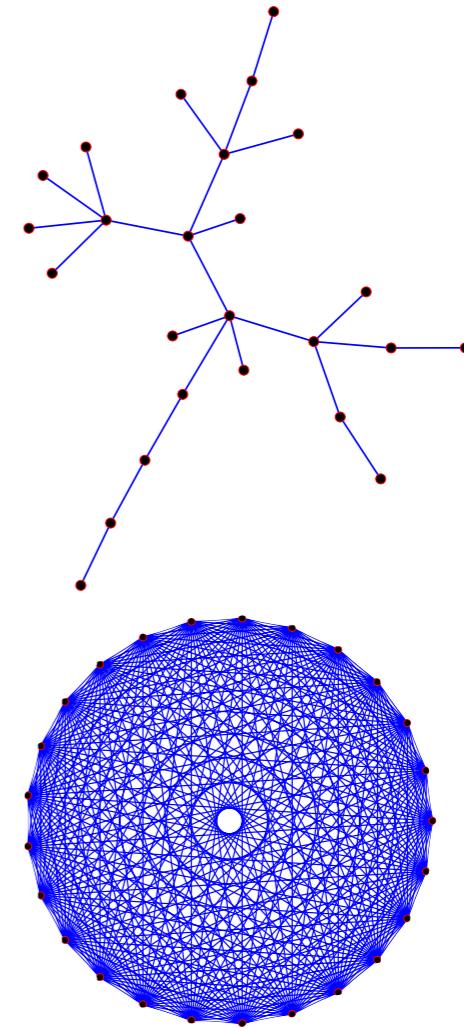
$$\|\Sigma_e(\mathcal{G})\|_2^2 = \frac{1}{2} \text{tr} \left[(R_{(\mathcal{T}, \mathcal{C})} R_{(\mathcal{T}, \mathcal{C})}^T)^{-1} \right] + (n - 1)$$

some immediate bounds...

$$\|\Sigma_e(\mathcal{G})\|_2^2 \leq \|\Sigma_e(\mathcal{T})\|_2^2 = \frac{3}{2}(n - 1)$$

all trees are the same

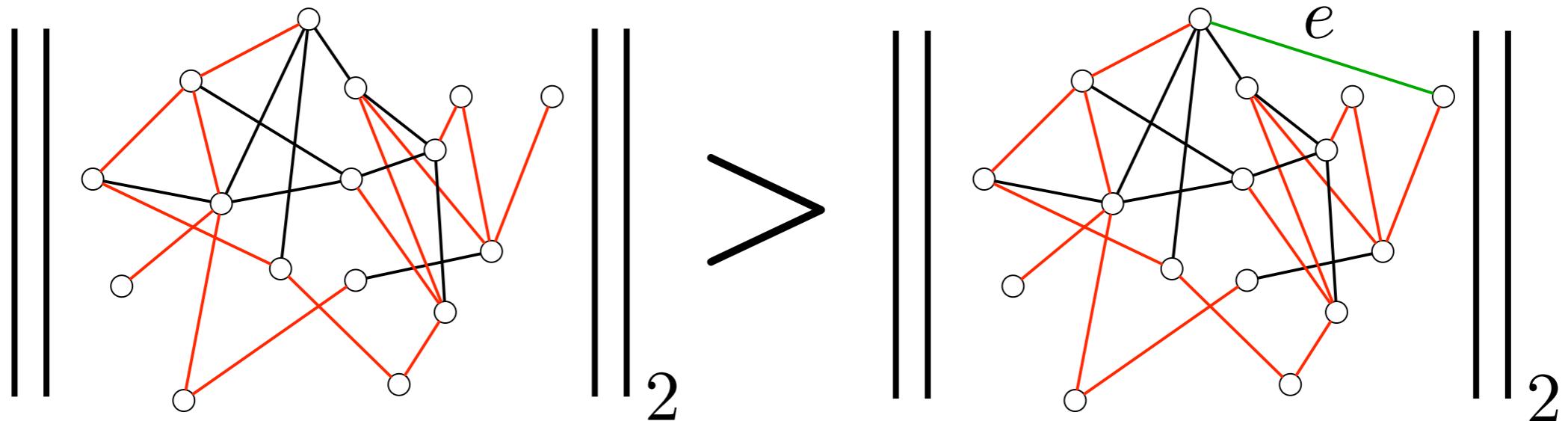
$$\|\Sigma_e(\mathcal{G})\|_2^2 \geq \|\Sigma_e(K_n)\|_2^2 = \frac{n^2 - 1}{n}$$



Performance and Cycles

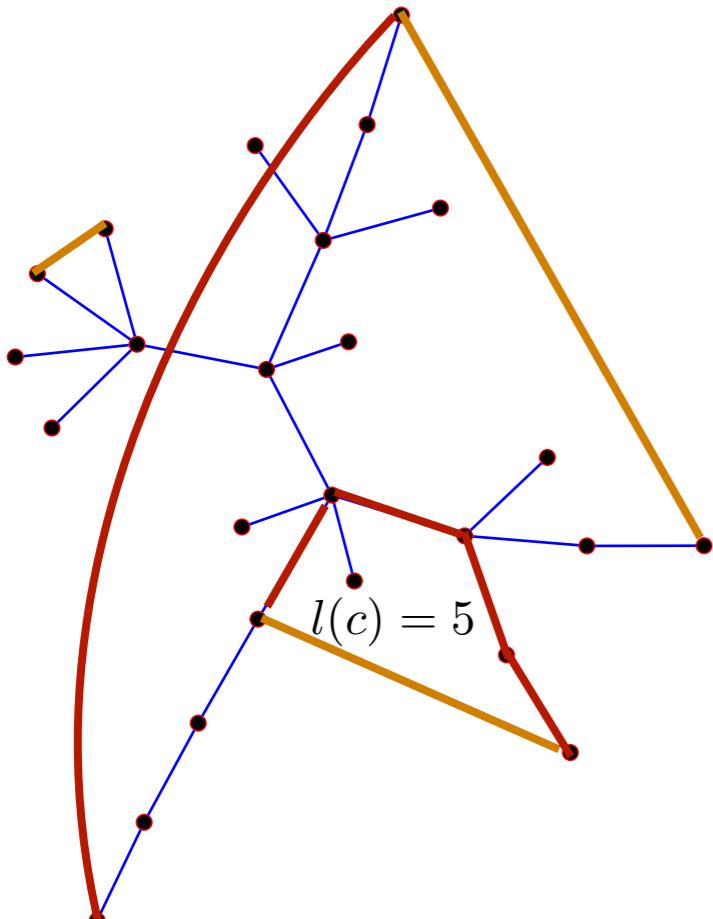
Theorem: Adding cycles always improves the performance.

$$\begin{aligned}\|\Sigma_e(\mathcal{G} \cup e)\|_2^2 &= \|\Sigma_e(\mathcal{G})\|_2^2 - \\ &\frac{\left(R_{(\tau,c)} R_{(\tau,c)}^T\right)^{-1} c c^T \left(R_{(\tau,c)} R_{(\tau,c)}^T\right)^{-1}}{2(1 + c^T \left(R_{(\tau,c)} R_{(\tau,c)}^T\right)^{-1} c)}\end{aligned}$$



Performance and Cycles

Is there a *combinatorial* feature
that affects the performance?



Corollary

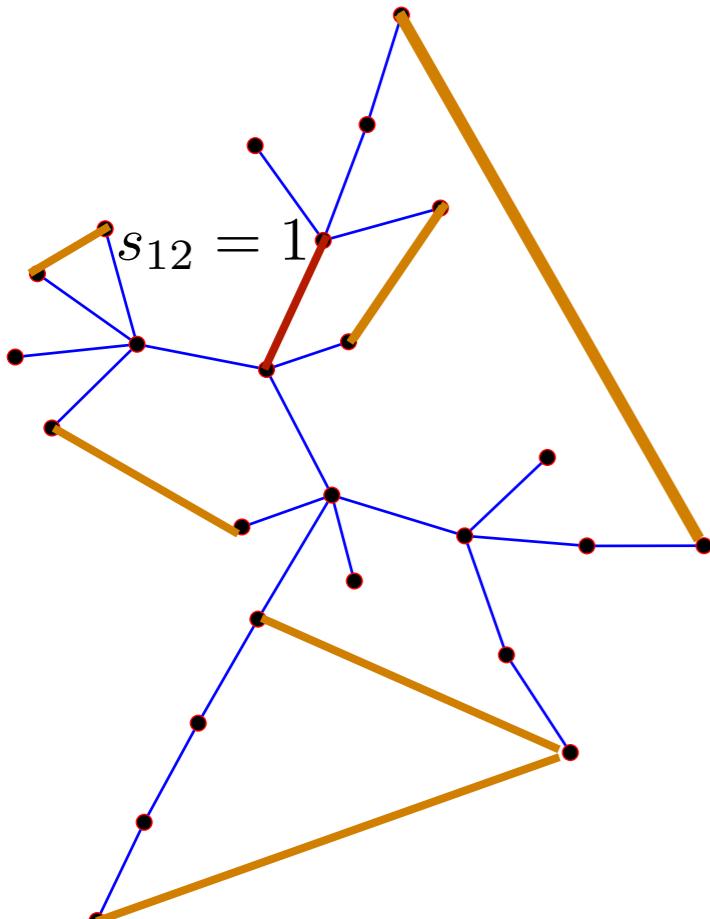
$$\|\Sigma_e(\mathcal{T} \cup e)\|_2^2 = \|\Sigma_e(\mathcal{T})\|_2^2 - \frac{1}{2}(1 - l(c)^{-1})$$

long cycles are “better”



Performance and Cycles

Is there a *combinatorial* feature
that affects the performance?



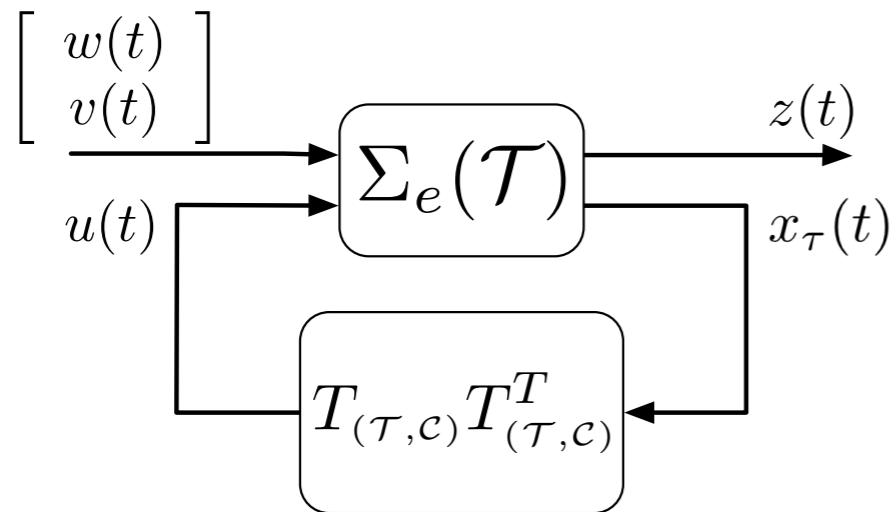
Corollary

$$\|\Sigma_e(\mathcal{T} \cup \{e_1, e_2\})\|_2^2 = \|\Sigma_e(\mathcal{T})\|_2^2 - \left(1 - \frac{l(c_1) + l(c_2)}{2(l(c_1)l(c_2) - s_{12}^2)}\right)$$

“edge disjoint” cycles are better



Design of Cycles



$$\min_{T_{(\tau,c)} \in \mathbb{R}^{|\mathcal{V}| \times k}} \|\Sigma_e(\mathcal{G})\|_2,$$

Given a spanning tree, add k edges that maximize the performance improvement

a mixed-integer SDP

$$\begin{aligned} & \min_{M, w_i} \quad \text{trace}[M] \\ \text{s.t.} \quad & \begin{bmatrix} M & I \\ I & I + T_{(\tau, \bar{\tau})} W T_{(\tau, \bar{\tau})} \end{bmatrix} \geq 0 \\ & \sum_i w_i = k, \quad w_i \in \{0, 1\} \end{aligned}$$



Design of Cycles

a mixed-integer SDP

$$\min_{M, w_i} \text{trace}[M]$$

s.t.

$$\begin{bmatrix} M & I \\ I & I + T_{(\mathcal{T}, \bar{\mathcal{T}})} W T_{(\mathcal{T}, \bar{\mathcal{T}})} \end{bmatrix} \geq 0$$

$$\sum_i w_i = k, \quad w_i \in \{0, 1\} \quad w_i \in [0, 1]$$

relaxation to *weighted* edges “misses the point”

$$\min_{M, w_i} \text{trace}[M] + \text{card}(w)$$



s.t.

$$\begin{bmatrix} M & I \\ I & I + T_{(\mathcal{T}, \bar{\mathcal{T}})} W T_{(\mathcal{T}, \bar{\mathcal{T}})} \end{bmatrix} \geq 0$$

$$\sum_i w_i = k, \quad w_i \in [0, 1]$$

attempt to minimize “# of non-zero elements”

not a convex relaxation!

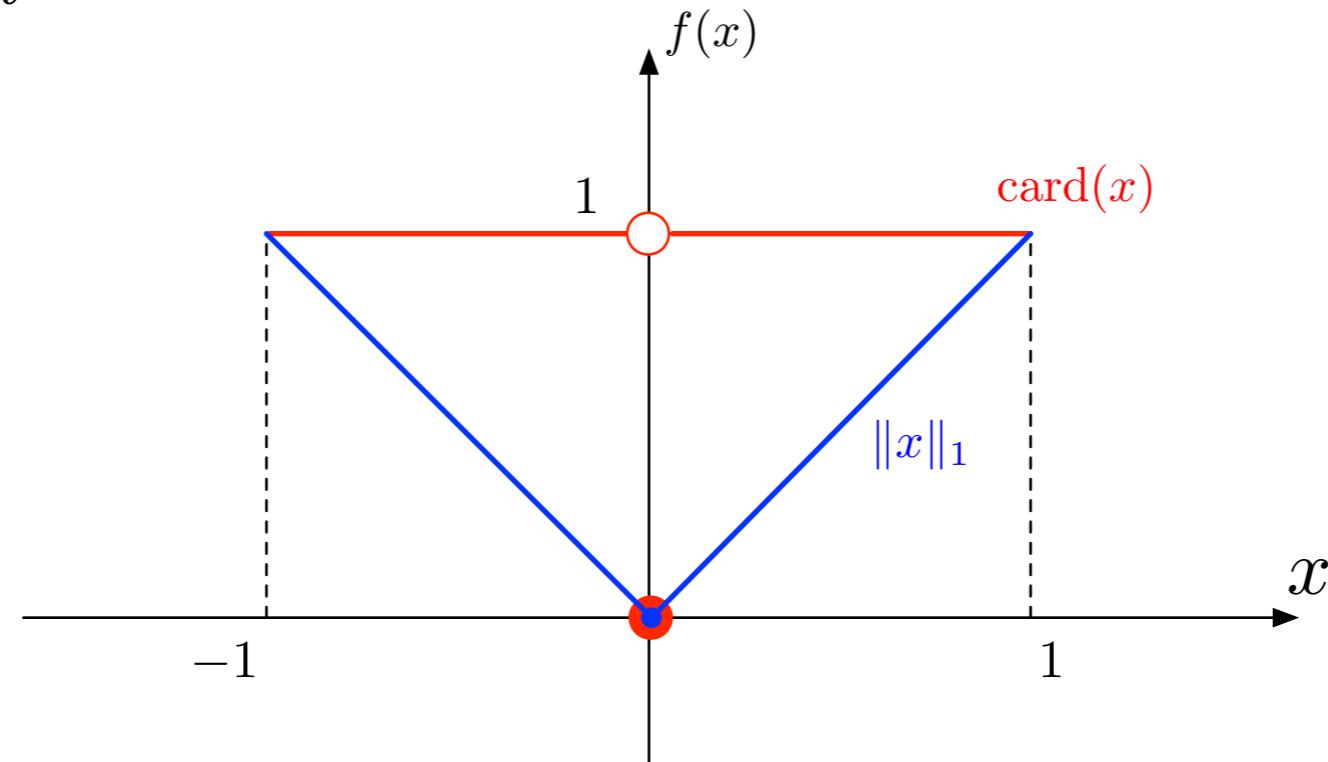


Convex Envelope of Cardinality

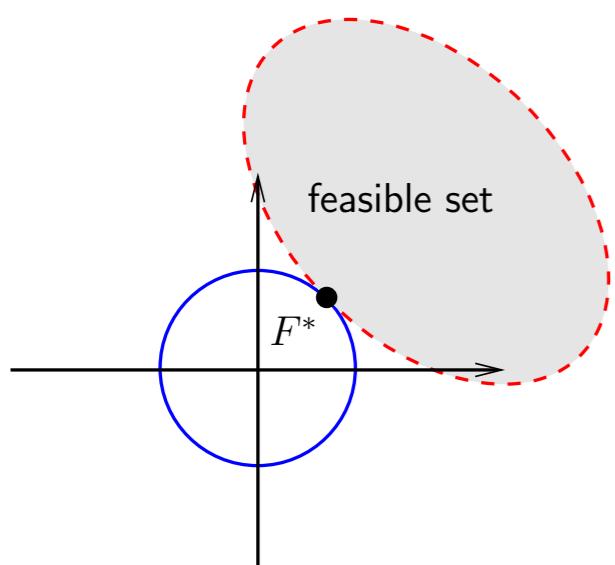
Definition. The convex envelope, f^{env} , of a function f on a set C is the (point-wise) largest convex function that is an under estimator of f on C .

example

$\|x\|_1 = \sum_i |x_i|$ is convex envelope of $\text{card}(x)$.

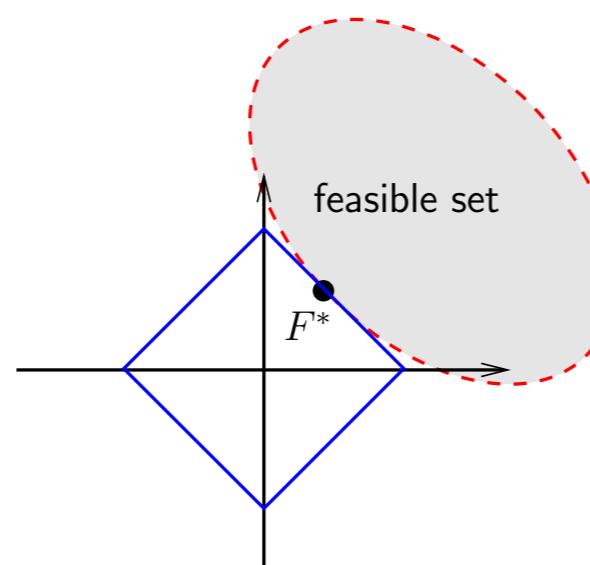


Sparsity Promoting Optimization



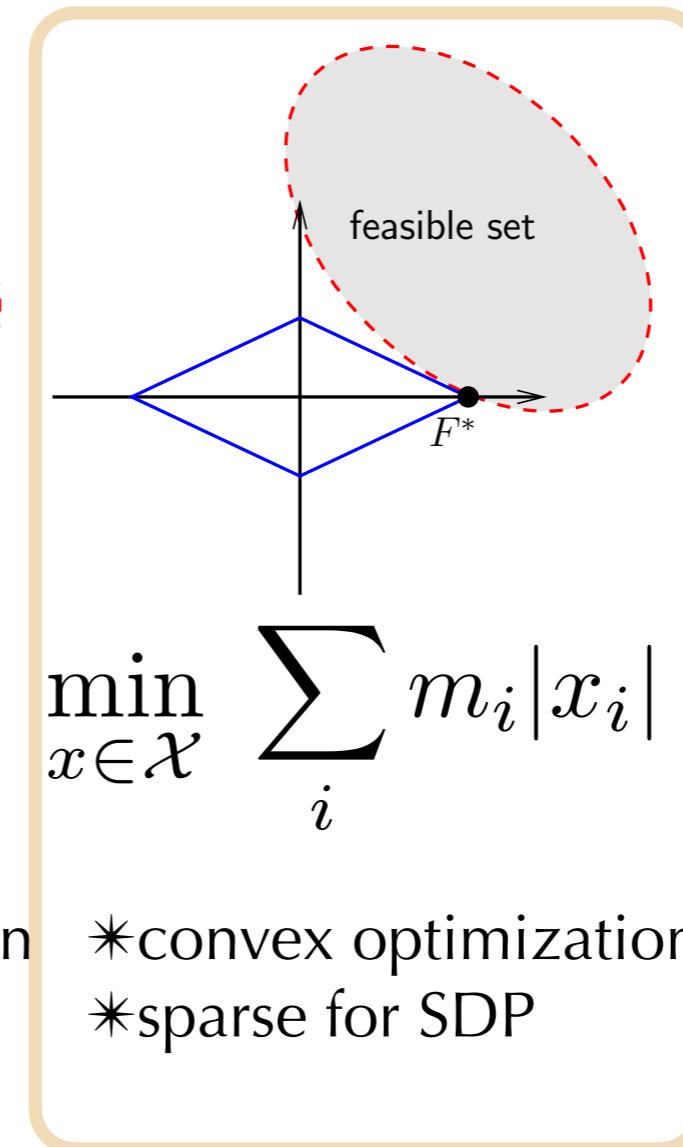
$$\min_{x \in \mathcal{X}} \|x\|_2$$

*convex optimization
*not sparse

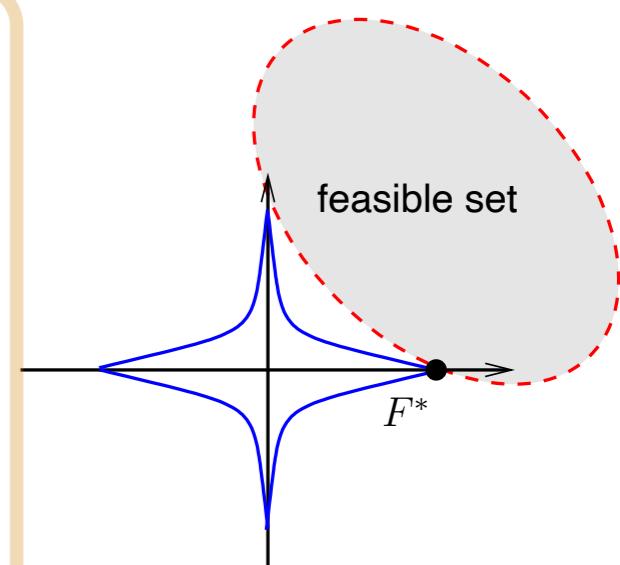


$$\min_{x \in \mathcal{X}} \|x\|_1$$

*convex optimization
*sparse for LP



*convex optimization
*sparse for SDP



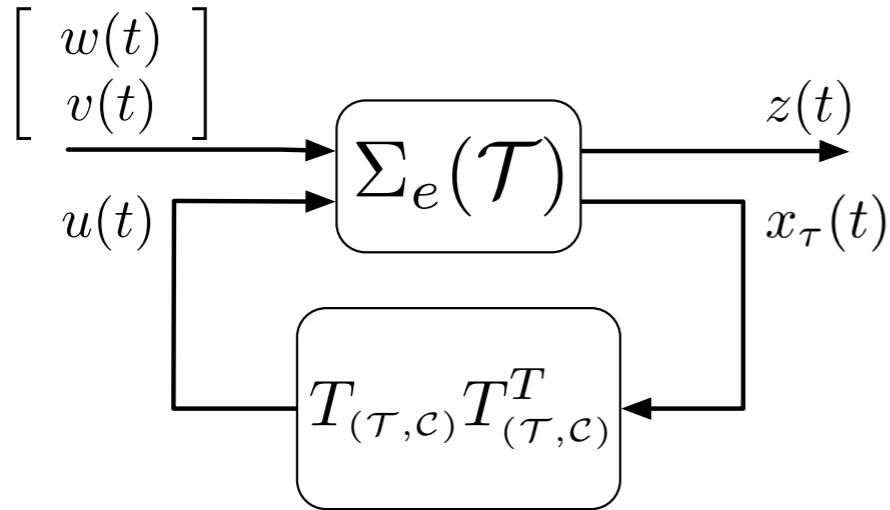
$$\min_{x \in \mathcal{X}} \|x\|_p$$

*non-convex
*sparse

re-weighted ℓ_1 minimization algorithm
[Candes 2008]



Design of Cycles



$$\min_{T_{(\tau,c)} \in \mathbb{R}^{|\mathcal{V}| \times k}} \|\Sigma_e(\mathcal{G})\|_2,$$

Given a spanning tree, add \mathbf{k} edges that maximize the performance improvement

$$\min_{M, w_i} \quad \alpha \text{trace}[M] + (1 - \alpha) \sum_i m_i w_i$$

$$\text{s.t.} \quad \begin{bmatrix} M & I \\ I & I + T_{(\tau, \bar{\tau})} W T_{(\tau, \bar{\tau})} \end{bmatrix} \geq 0$$

$$\sum_i w_i = k, \quad 0 \leq w_i \leq 1.$$



Design of Cycles

Re-weighted ℓ_1 minimization algorithm

① set counter $h = 0$

choose initial weights for each edge $m_i^{(0)}$

combinatorial
insights used here!

② solve convex program - obtain optimal weights $w_i^{(h)}$

$$\min_{M, w_i} \quad \alpha \text{trace}[M] + (1 - \alpha) \sum_i m_i^{(h)} w_i$$

$$\text{s.t.} \quad \begin{bmatrix} M & I \\ I & I + T_{(\tau, \bar{\tau})} W T_{(\tau, \bar{\tau})} \end{bmatrix} \geq 0$$

$$\sum_i w_i = k, \quad 0 \leq w_i \leq 1.$$

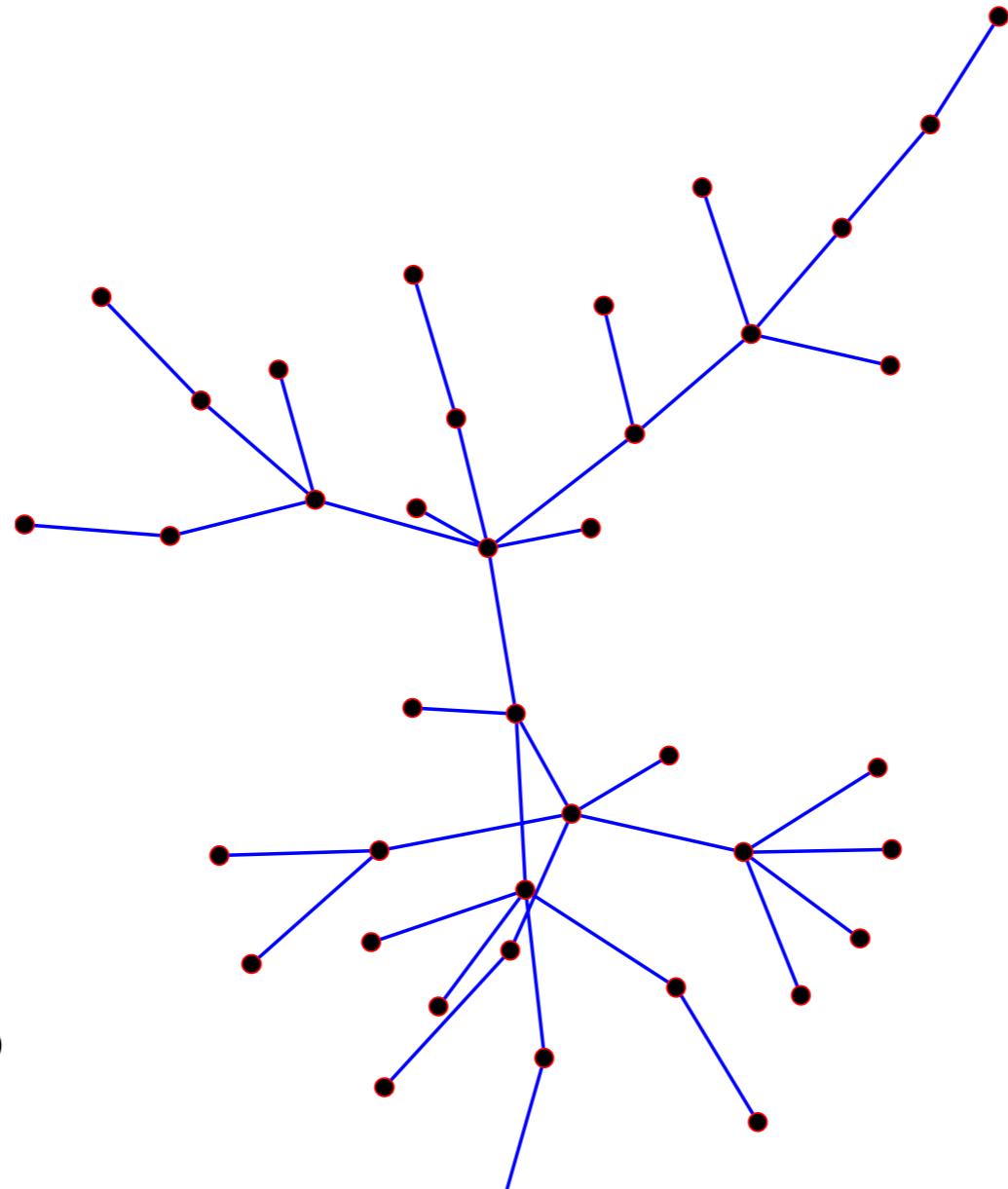
③ update weights $m_i^{(h+1)} = (w_i^{(h)} + \nu)^{-1}$

④ terminate on convergence, or
increment counter and go to step 2

[Candes 2008]



Simulation Examples



spanning tree
30 nodes

741 candidate
edges

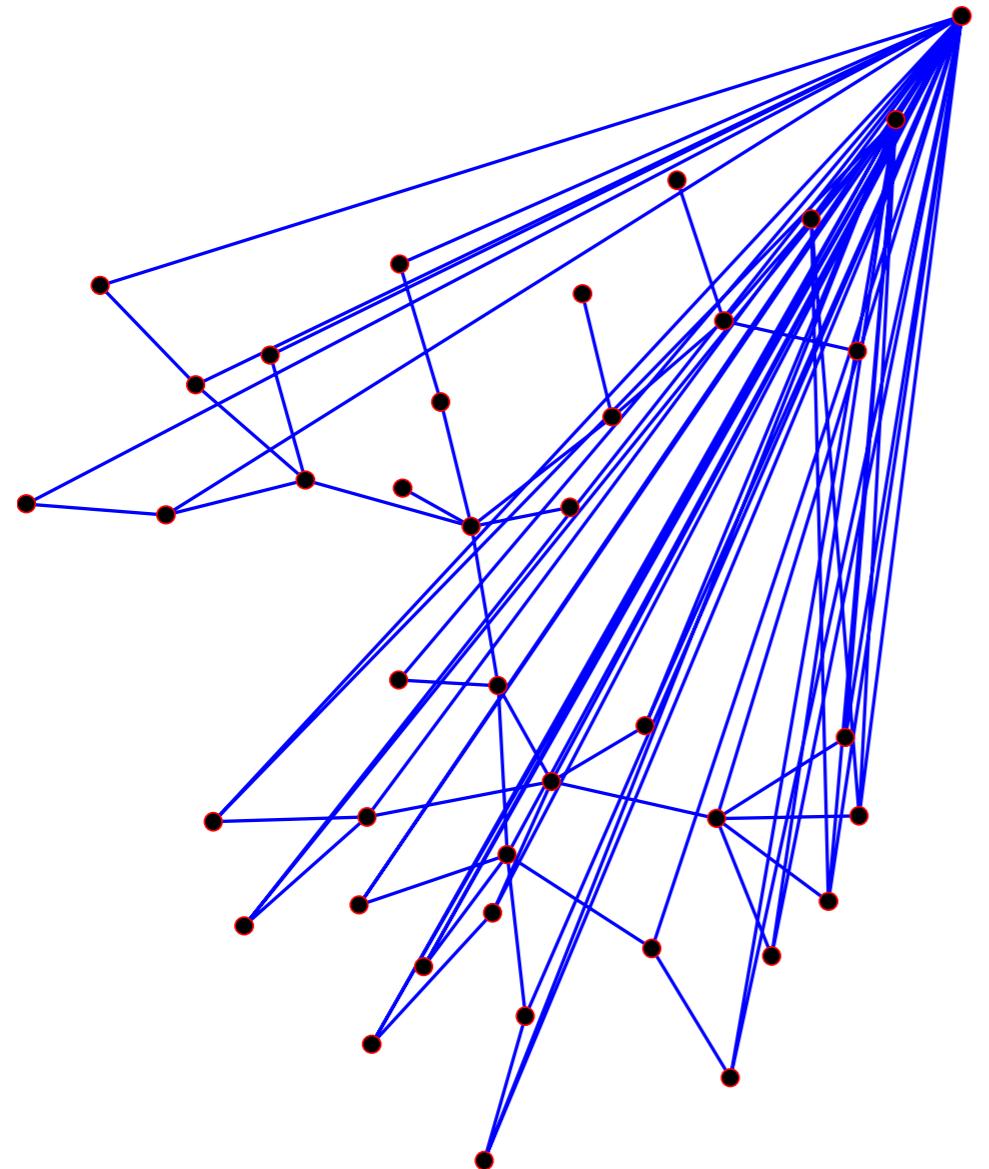
add 40 new
edges

$$\|\Sigma(\mathcal{T})\|_2^2 = 58.5$$

$$\|\Sigma(K_n)\|_2^2 = 39.975$$



Simulation Examples



weights can be used to promote certain graph properties

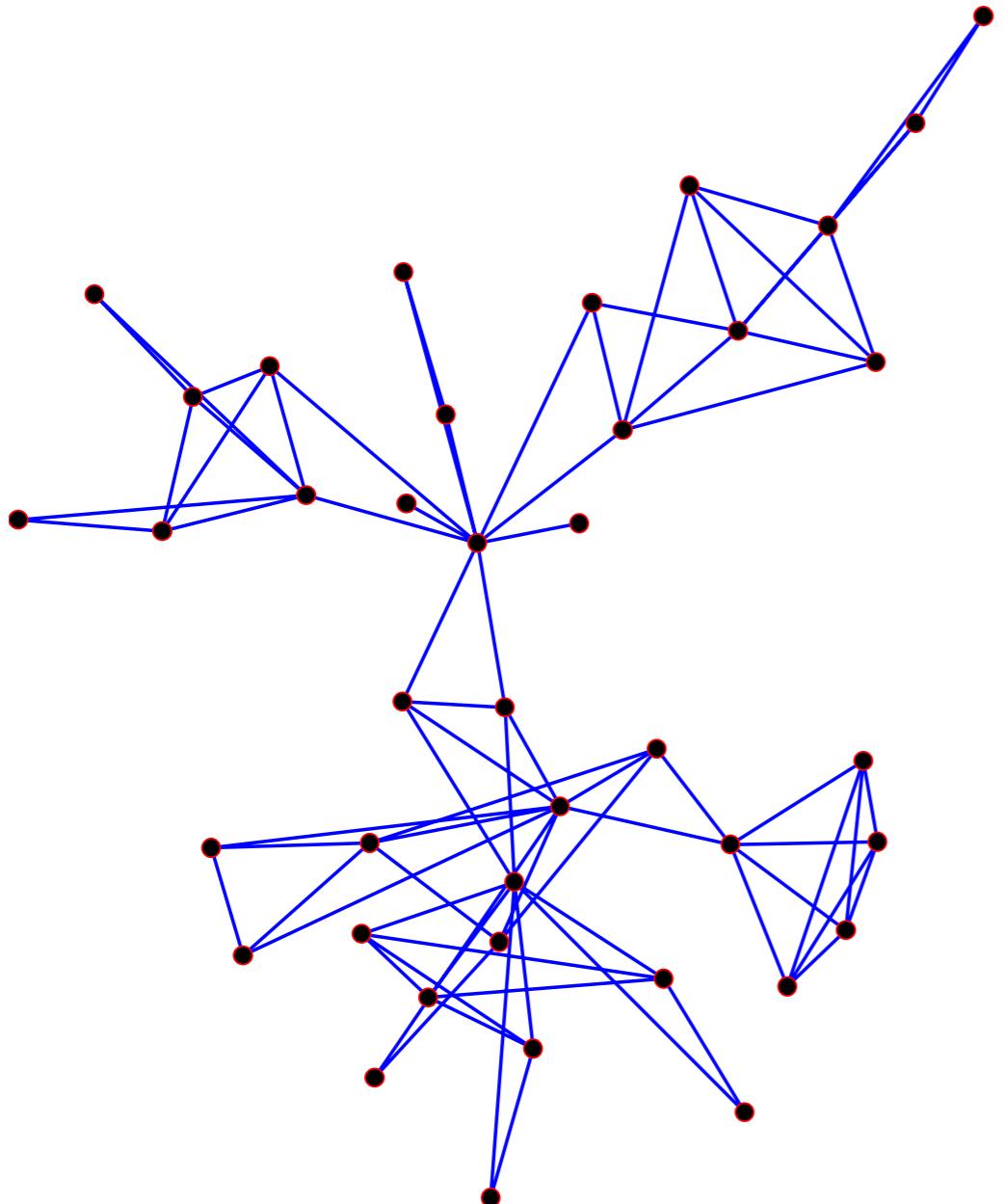
“long cycle weights”

$$m_i = \text{diam}(\mathcal{G}) - \|c_i\|_1 + 1$$

$$\|\Sigma(\mathcal{G})\|_2^2 = 50.233$$



Simulation Examples



weights can be used to promote certain graph properties

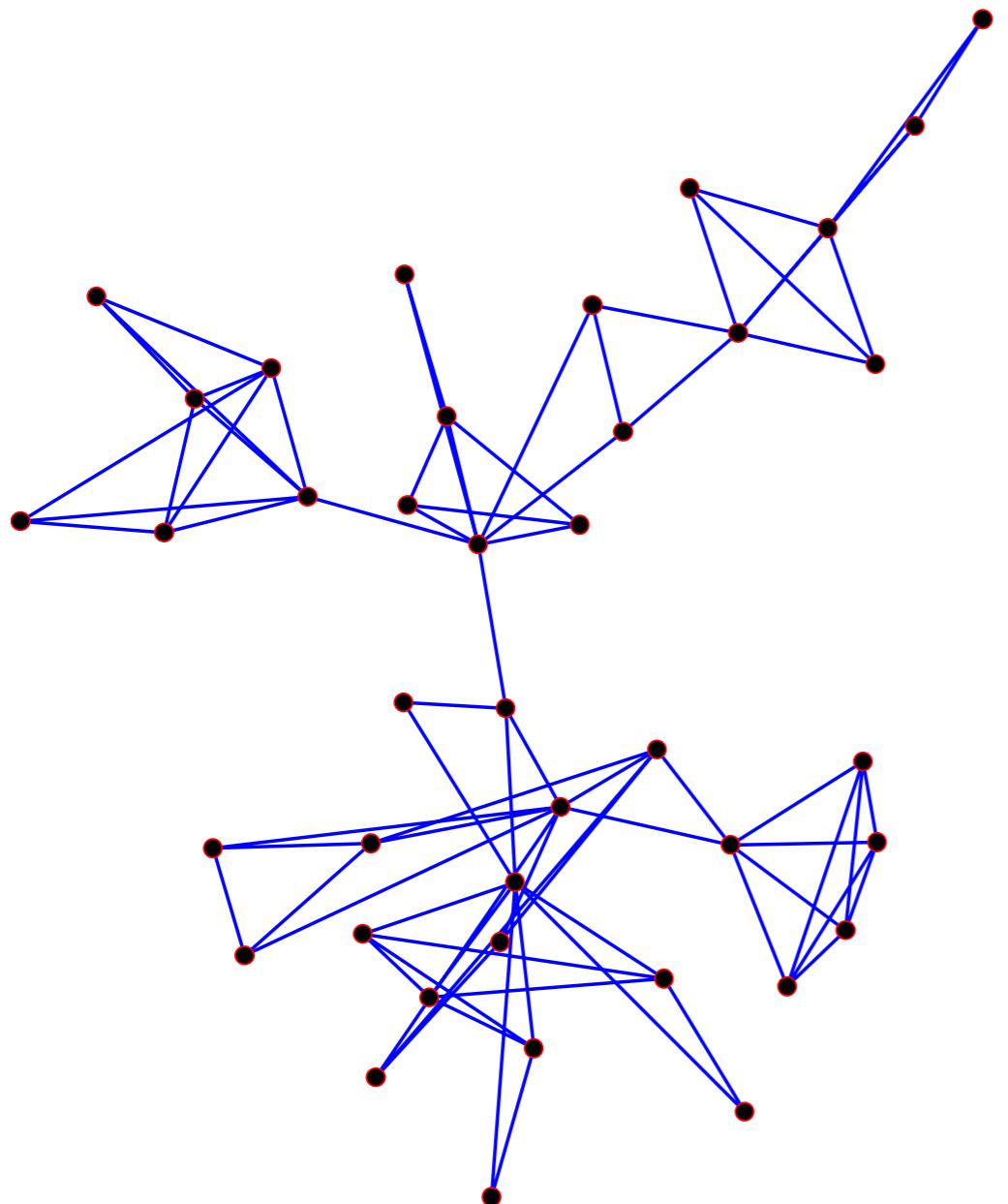
“short cycle weights”

$$m_i = \|c_i\|_1$$

$$\|\Sigma(\mathcal{G})\|_2^2 = 48.704$$



Simulation Examples



weights can be used to promote certain graph properties

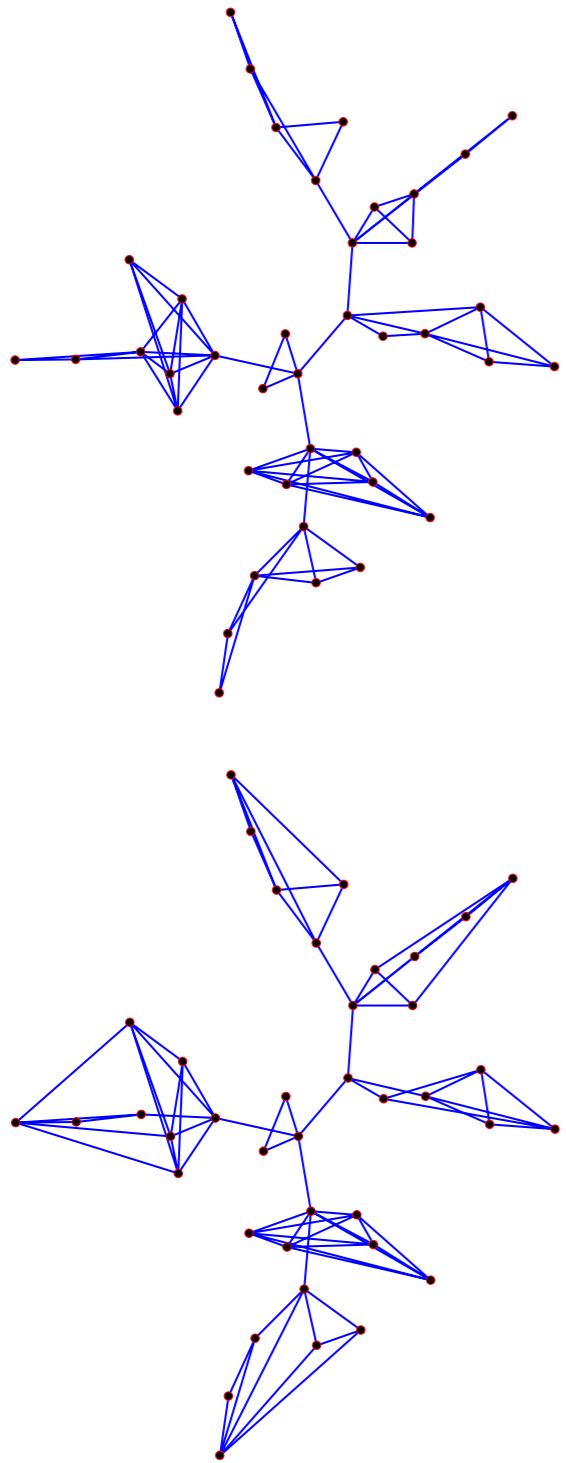
“cycle correlation weights”

$$m_i = \frac{1}{|\mathcal{E}_c|} \sum_{j \neq i} \left| [T_{(\mathcal{T}, c)} T_{(\mathcal{T}, c)}^T]_{ij} \right|$$

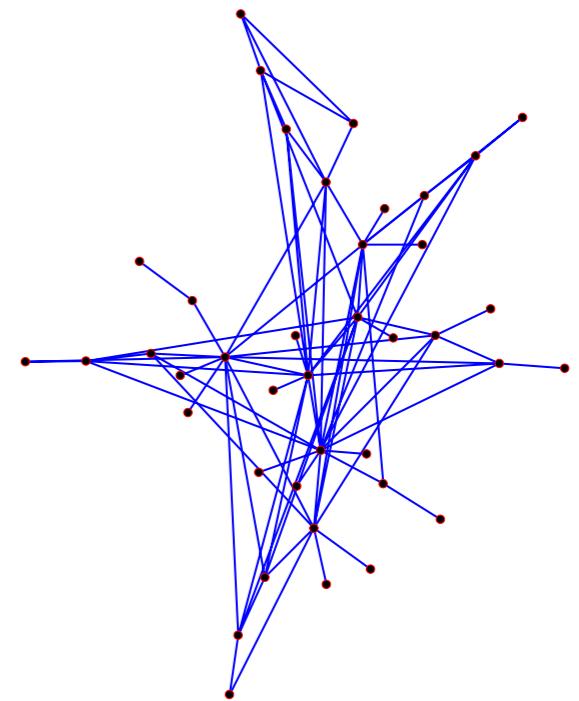
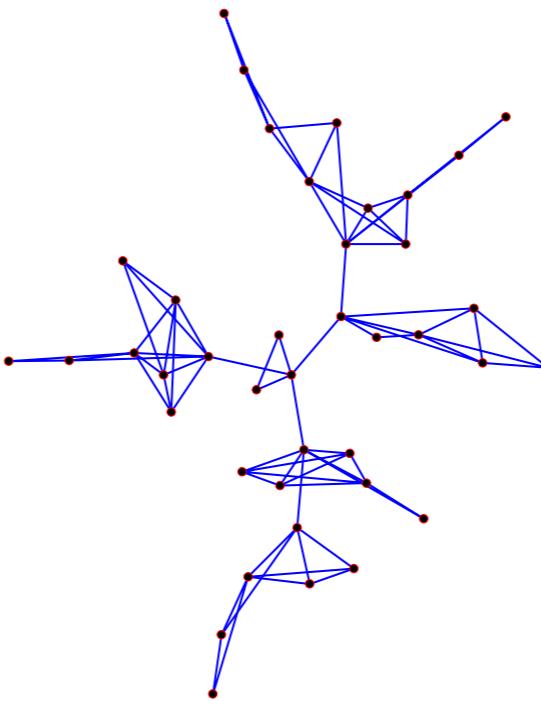
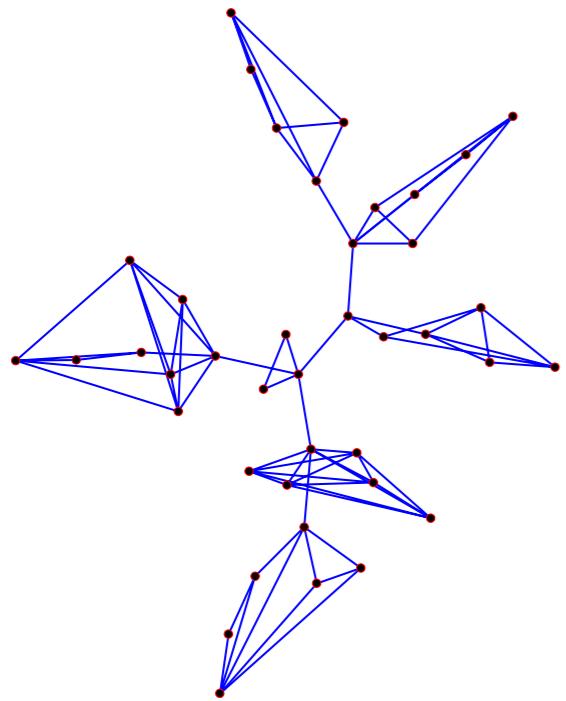
$$\|\Sigma(\mathcal{G})\|_2^2 = 48.939$$



Simulation Examples



weights can be used to promote certain graph properties



Concluding Remarks

role of cycles in consensus networks

- * internal feedback
- * performance

a tractable design procedure

- * l1 optimization
- * design of multi-agent systems

future works

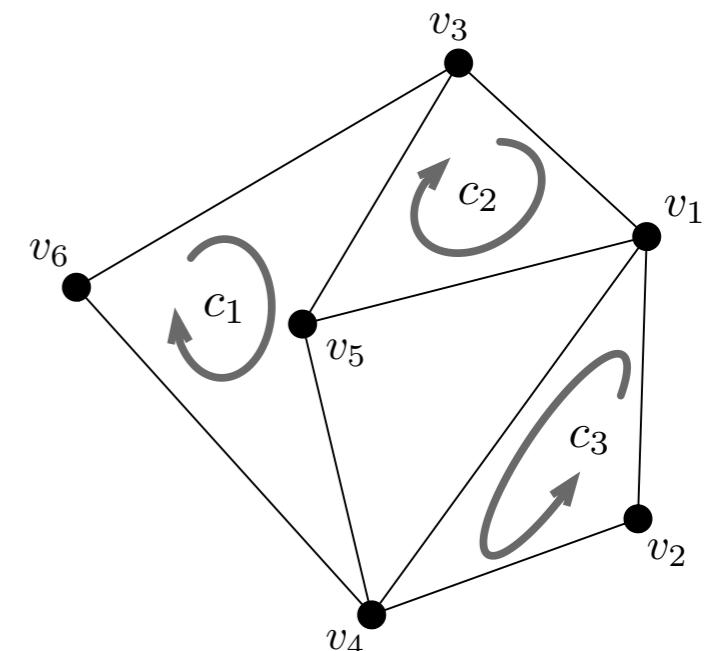
- * additional performance metrics
- * push to large scale

**Performance and design of cycles in consensus networks”

Systems & Control Letters 62(1) : 85-96, 2013.

**Edge Agreement: Graph-theoretic Performance Bounds and Passivity Analysis”

IEEE Transactions on Automatic Control 56(3) : 554-555, 2011.



Concluding Remarks

謝謝



Prof. Dr. -Ing. Frank Allgöwer



Simone Schuler

Questions?



הפקולטה להנדסת אירונוטיקה וחלל

Faculty of Aerospace Engineering

NCEPU September 2, 2013,
Beijing, China