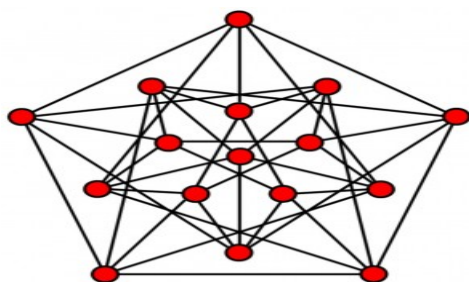


Como, Italy, October 2022



DIGRAPHS IV
Chemical Networks
The Matrix Tree Theorem

Based on various sources, among which:
J. J. P. Veerman, T. Whalen-Wagner, E. Kummel
*Chemical Reaction Networks in a Laplacian
Framework, Chaos, Solitons, and Fractals,*
accepted, 2022.

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SUMMARY:

- * We differential equations governing the behavior of chemical reaction networks can be built up using the boundary operators. This gives rise, very naturally, to a Laplacian formulation of the dynamics.
- * These differential equations are *nonlinear*. In spite of that, in many cases, the Laplacian approach can be used to describe the global dynamics of the network.
- * Matrix tree theorems connect different branches of mathematics (combinatorics, linear algebra, probability) in unexpected ways. For this reason, they play an important role in the graph theory literature.
- * We give a detailed description of various matrix tree theorems. These theorems relate the determinant of certain submatrices of the usual Laplacian to the number of spanning trees rooted at each vertex.
- * We give a simple, short, combinatorial proof loosely inspired by [1].
- * We include a discussion that relates the number of spanning trees at each vertex to the stable probability measure of random walk on a strongly connected graph.

OUTLINE:

The headings of this talk are color-coded as follows:

Boundary Operators

Chemical Reaction Networks

The Zero Deficiency Theorem

Example and Further Developments

Matrix Tree Theorems

Proof of Matrix Tree Theorems

Trees and Unicycles

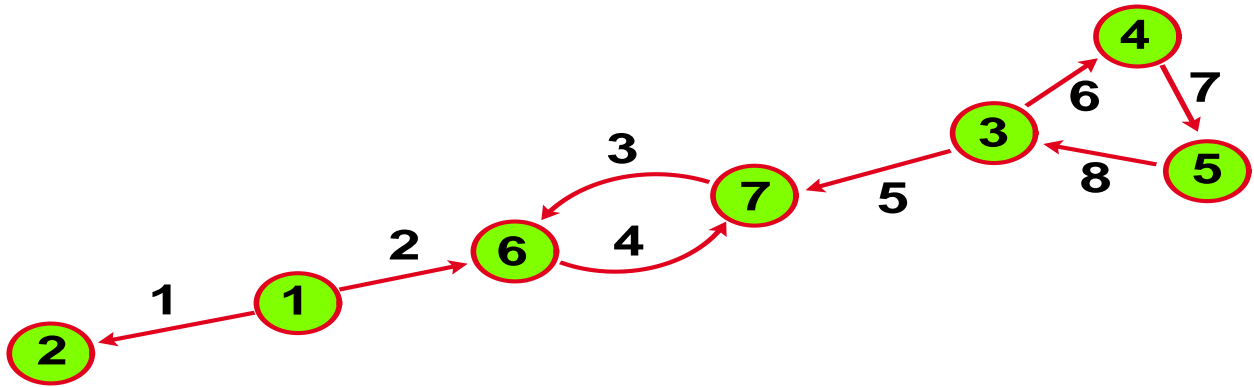
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BOUNDARY OPERATORS

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The Boundary Matrices



Definition: Given a digraph G , define matrices B (for Begin) and E (for End), as maps Edges \rightarrow Vertices.

$$E_{ij} = \begin{cases} 1 & \text{if vertex } i \text{ ends edge } j \\ 0 & \text{else} \end{cases}$$

$$B_{ij} = \begin{cases} 1 & \text{if vertex } i \text{ starts edge } j \\ 0 & \text{else} \end{cases}$$

$$E = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \mathbf{1} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{1} \\ 0 & 0 & 0 & 0 & 0 & \mathbf{1} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{1} & 0 \\ 0 & \mathbf{1} & \mathbf{1} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \mathbf{1} & \mathbf{1} & 0 & 0 & 0 \end{pmatrix} \quad B = \begin{pmatrix} \mathbf{1} & \mathbf{1} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \mathbf{1} & \mathbf{1} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{1} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{1} \\ 0 & 0 & 0 & \mathbf{1} & 0 & 0 & 0 & 0 \\ 0 & 0 & \mathbf{1} & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

Edges are columns. Vertices are rows.

Consistent with **definition** of boundary operator in topology:

$$\partial := E - B$$

From Boundary to Adjacency

Let v number of vertices. Want an operator mapping \mathbb{C}^v to itself. Thus EE^T , EB^T , BE^T , and BB^T are natural candidates. We investigate these operators.

FACT 1:

$$(\mathbf{EE}^T)_{ij} = \sum_k E_{ik}E_{jk}$$

is the # edges that end in i and in j .

Thus it is the **diagonal in-degree matrix**.

Similarly, **\mathbf{BB}^T** is the **diagonal out-degree matrix**.

FACT 2:

$$(\mathbf{EB}^T)_{ij} = \sum_k E_{ik}B_{jk}$$

is the # edges that start in j and end in i .

It is the **comb. in-degree adj. matrix** Q (as in DI).

And **\mathbf{BE}^T** is the **comb. out-degree adj. matrix** or Q^T .

Lemma: In the notation of DI, we have:

$$D = EE^T \quad \text{and} \quad Q = EB^T$$

Exercise: Check the facts as well as the ones mentioned for BB^T and BE^T .

Exercise: Interpret as operators $\mathbb{C}^e \rightarrow \mathbb{C}^e$ (e number of edges).

... and on to Laplacians

The Lemma immediately implies:

Theorem 1: In the notation of DI, we have:

$$L = E(E^T - B^T) \quad \text{and} \quad L_{\text{out}} = -B(E^T - B^T)$$

where L_{out} is the Laplacian of the graph G with all orientations reversed.

The example in the next pages illustrate the following two remarks.

Remark 1: Be careful to note that $L_{\text{out}} \neq L^T$!!

Remark 2: Note that the sum of L and L_{out} is the Lapl. of the underlying graph \underline{G} . Thus:

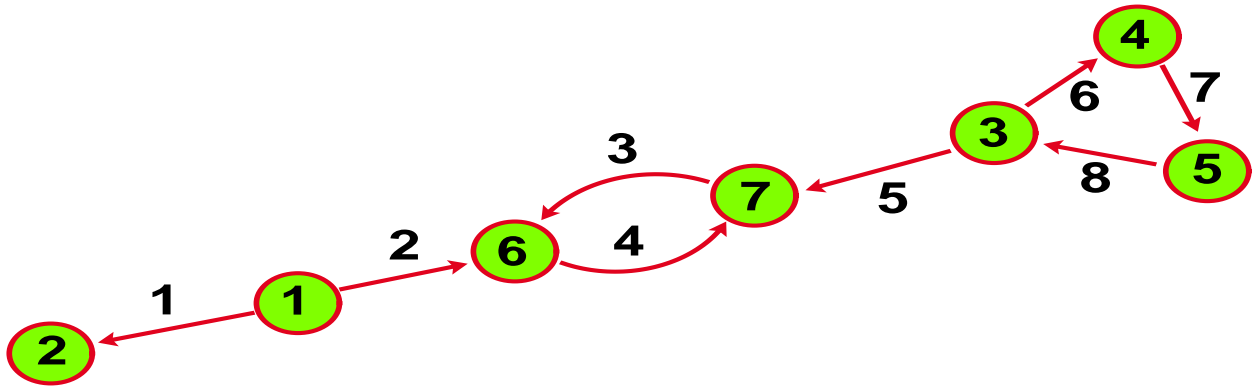
Corollary: We have:

$$\underline{L} = L + L_{\text{out}} = (E - B)(E^T - B^T) = \partial\partial^T$$

Remark: This is the traditional definition of the Laplacian in topology.

Re-Definition: L is the standard comb. Lapl. of the previous lectures. Better notation in this context: From now on, replace L by L_{in} ,

Example



$$L_{\text{in}} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & -1 & 0 & 0 \\ 0 & 0 & -1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & -1 & 1 & 0 & 0 \\ -1 & 0 & 0 & 0 & 0 & 2 & -1 \\ 0 & 0 & -1 & 0 & 0 & -1 & 2 \end{pmatrix}$$

$$L_{\text{out}} = \begin{pmatrix} 2 & -1 & 0 & 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 2 & -1 & 0 & 0 & -1 \\ 0 & 0 & 0 & 1 & -1 & 0 & 0 \\ 0 & 0 & -1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & -1 \\ 0 & 0 & 0 & 0 & 0 & -1 & 1 \end{pmatrix}$$

And $\underline{L} = L_{\text{in}} + L_{\text{out}}$ is symmetric. (Note that the edge between vertices 6 and 7 doubles or acquires weight 2 in this process.)

Exercise: Find these Laplacians from Theorem 1.

Linegraphs

$E^T B - 2I$ and $B^T E - 2I$ give versions of the adjacency matrix of the linegraph of G . This needs working out. See the Graph Theory handbook page 679.

Weighted Laplacians

Definition: We can “weight” the edges. Let W be a diagonal weight matrix.

$$L_{\text{in},W} = (EW)(E^T - B^T)$$

We drop the subscript “ W ”. In particular

$$\mathcal{L}_{\text{in}} = (ED^{-1})(E^T - B^T)$$

where $D_{ii} = 1$ if the in-degree in 0. (see DI)

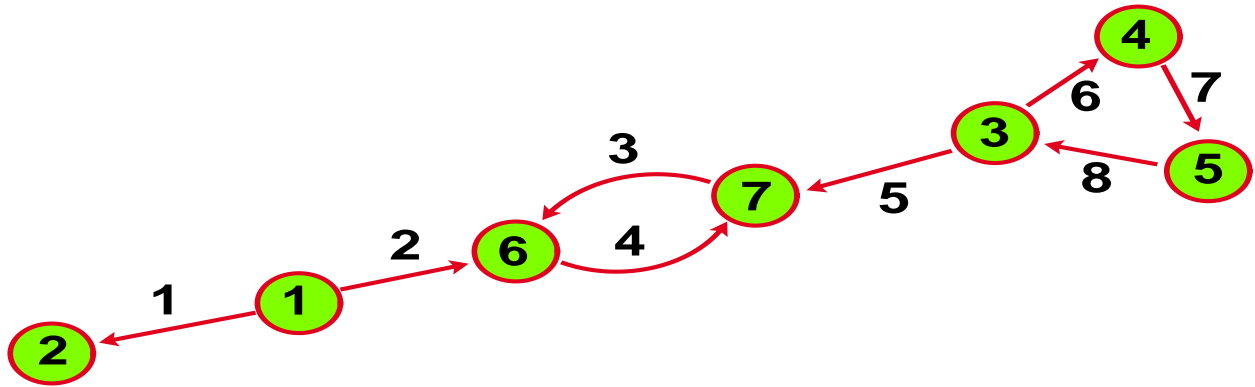
Remark: Note that

$$[(EW)B^T]_{ij} = \sum_k E_{ik}W_{kk}B_{jk}$$

which means the weights go to the edges (not the vertices).

Be careful: The symbol \mathcal{L}_{out} is reserved for the out-degree rw Laplacian. The edges have a weight different from that of \mathcal{L}_{in} . See example.

Example with Weights

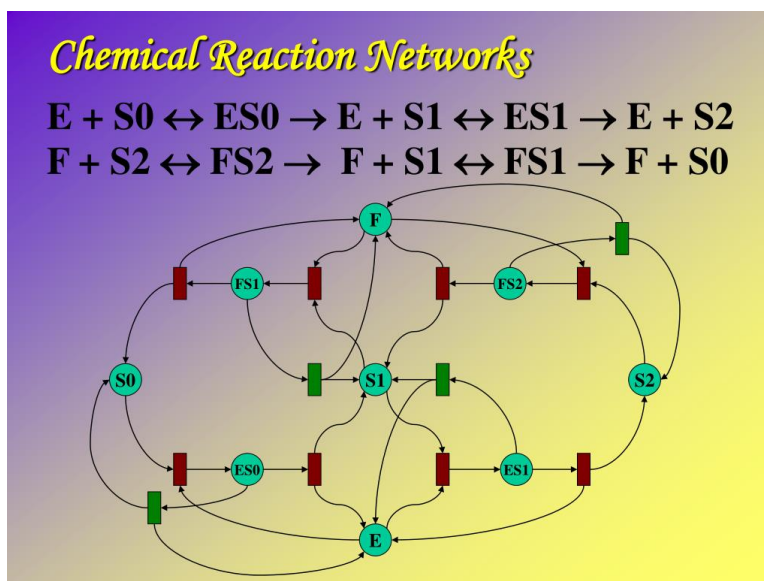


$$\mathcal{L}_{\text{in}} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & -1 & 0 & 0 & 0 \\ 0 & 0 & -1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -1 & 1 & 0 & 0 & 0 \\ -1/2 & 0 & 0 & 0 & 0 & 1 & -1/2 & 0 \\ 0 & 0 & -1/2 & 0 & 0 & -1/2 & 1 & 0 \end{pmatrix}$$

$$\mathcal{L}_{\text{out}} = \begin{pmatrix} 1 & -1/2 & 0 & 0 & 0 & -1/2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & -1/2 & 0 & 0 & 0 & -1/2 \\ 0 & 0 & 0 & 1 & -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & -1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & -1 & 0 \\ 0 & 0 & 0 & 0 & 0 & -1 & 1 & 0 \end{pmatrix}$$

Notice that the sum of these two is NOT symmetric. Edge 6 ($\mathcal{L}_{\text{in},4,3}$ and $\mathcal{L}_{\text{out},3,4}$) received two different weights in each case.

CHEMICAL REACTION NETWORKS OR CRN



From a presentation by David Angeli, Univ of Firenze, Italy.
Chemical networks can have thousands of vertices.

A Simple Example



Concentrations of $C + O_2$ is an ambiguous concept.

Can measure only concentrations of molecules: H_2O , H_2 etc.

Set x_i equal to concentration of following molecules:

$$x_1 \leftrightarrow H_2, x_2 \leftrightarrow O_2, x_3 \leftrightarrow H_2O, x_4 \leftrightarrow C, x_5 \leftrightarrow CO_2$$

Assume all molecules are unif. distr. in the mix.

Observation 1. Reaction 1 says: for every 2 molecules H_2 and 1 molecule O_2 that react we get 2 molecules H_2O back.

Observation 2. Reaction rate is proportional to the chance that that the reacting molecules “meet”. For reaction 1 that is $x_1^2 x_2$. The constant of the proportionality is called k_1 .

The same for reaction 2. So:

$$\dot{x}_1 = -2k_1 x_1^2 x_2$$

$$\dot{x}_2 = -2k_1 x_1^2 x_2 - k_2 x_2 x_4$$

$$\dot{x}_3 = 2k_1 x_1^2 x_2$$

$$\dot{x}_4 = -k_2 x_2 x_4$$

$$\dot{x}_5 = k_2 x_2 x_4$$

Observation 2 is called the **mass action principle**.

The Basic Idea ...

Definition: (conc. means concentration)

\mathbb{R}^c	“conc.s of molecules”	variables x_i
\mathbb{R}^v	“conc.s of reacting mixtures”	variables v_i
\mathbb{R}^e	“reactions”	denoted by e_i

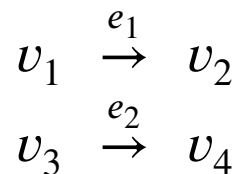
Relevant Operators:

$$\begin{aligned}
 & \psi \text{ (non-linear)} & : & \mathbb{R}^c \rightarrow \mathbb{R}^v \\
 E, B \text{ (linear)} & : & \mathbb{R}^e \rightarrow \mathbb{R}^v & \quad \text{and} \quad E^T, B^T : \mathbb{R}^v \rightarrow \mathbb{R}^e \\
 & S \text{ (linear)} & : & \mathbb{R}^v \rightarrow \mathbb{R}^c
 \end{aligned}$$

Key Idea 1. Use mass action to give ode for conc.s of $\{x_i\}_1^c$.

$$\mathbb{R}^c \xleftarrow{S} \mathbb{R}^v \xleftarrow{\partial=E-B} \mathbb{R}^e \xleftarrow{W} \mathbb{R}^e \xleftarrow{B^T} \mathbb{R}^v \xleftarrow{\psi} \mathbb{R}^c$$

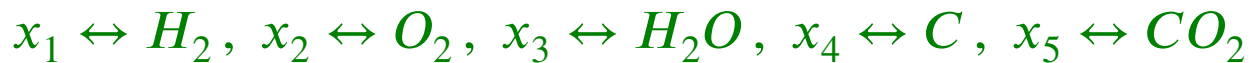
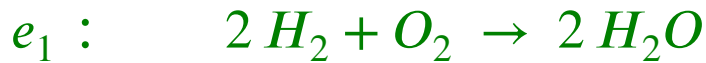
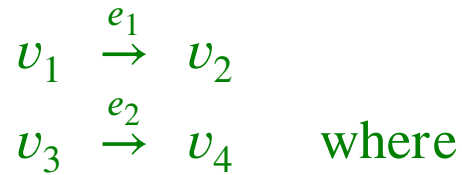
Key Idea 2. Form a **network** by putting together the reactions $v_i \xrightarrow{e_\ell} v_j$ with the v_i as its vertices. Our example:



v_1 is the conc. of the **reacting mixture**, i.e. $2H_2 + O_2$, etc.

Look at the associated Laplacian !!!

... and Some Details



Definition: The count of i -molecules (belonging x_i) in the j th vertex v_j equals S_{ij} . S has no zero rows. Rate of change \dot{x}_i equals the sum of rates of change of those mixtures in which that molecule occurs.

$$\dot{x} = S\dot{v} \quad \text{or} \quad \dot{x}_j = \sum_i S_{ji}\dot{v}_i.$$

Exercise: Show that for our example

$$S = \begin{pmatrix} 2 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 0 & 2 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

and Apply Mass Action

Mass Action Lemma. The probability ψ_i that all molecules in v_i “meet” is

$$\psi_i(x) \equiv \prod_j x_j^{S_{ji}}$$

Exercise: Show that if $x > 0$, then $\text{Ln } \psi(x) = S^T \text{Ln } x$.

Exercise: Show that for this example

$$\psi_1 = x_1^2 x_2, \quad \psi_2 = x_3^2, \quad \psi_3 = x_2 x_4, \quad \psi_4 = x_5$$

Putting the Equations Together

Prescription 1: Form the diff eqns as follows:

$\mathbb{R}^c \rightarrow \mathbb{R}^v$;	convert conc.s to mass action terms;	ψ
$\mathbb{R}^v \rightarrow \mathbb{R}^e$;	assign initial m.a. term to each edge;	B^T
$\mathbb{R}^e \rightarrow \mathbb{R}^e$;	weight each e_i by its reaction rate;	W
$\mathbb{R}^e \rightarrow \mathbb{R}^v$;	add @endvertex, subtr. @startvertex;	$E - B$
$\mathbb{R}^v \rightarrow \mathbb{R}^c$;	convert to conc. of molecules;	S

$$\begin{array}{ccccccc}
 \mathbb{R}^c & \xleftarrow{S} & \mathbb{R}^v & \xleftarrow{\partial=E-B} & \mathbb{R}^e & \xleftarrow{W} & \mathbb{R}^e & \xleftarrow{B^T} & \mathbb{R}^v & \xleftarrow{\psi} & \mathbb{R}^c \\
 & & & \underbrace{\hspace{10em}} & & & & & & & \\
 & & & & -L_{\text{out}}^T & & & & & &
 \end{array}$$

Prescription 2: Recall out-degree Lapl. (Thm 1), so that

$$\dot{\mathbf{x}} = -S L_{\text{out}}^T \psi(\mathbf{x})$$

Exercise: Compute B , E , and W for this example.

Exercise: Use B , E , and W to compute L_{out} and L_{out}^T .

Exercise: Use S , ψ , and L_{out}^T to show that for the example:

$$\begin{aligned}
 \dot{x}_1 &= -2k_1 x_1^2 x_2 \\
 \dot{x}_2 &= -k_1 x_1^2 x_2 - k_2 x_2 x_4 \\
 \dot{x}_3 &= 2k_1 x_1^2 x_2 \\
 \dot{x}_4 &= -k_2 x_2 x_4 \\
 \dot{x}_5 &= k_2 x_2 x_4
 \end{aligned}$$

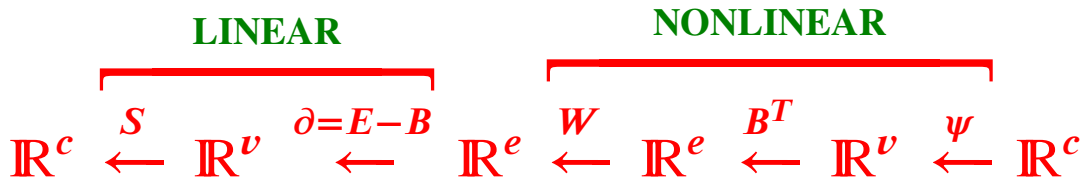
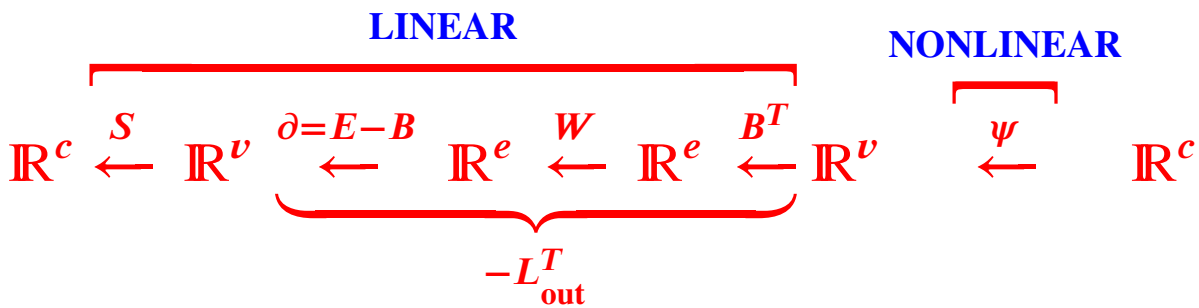
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D I F F E R E N C E
W I T H
E A R L I E R W O R K

Later is Better?

Since pioneering work by Horn, Jackson, and Feinberg in the 1970's [2, 3, 4], the split into nonlinear and linear parts has been different from what we propose.

Below the proposed split (blue) and the classical split (green).



The matrix W contains the reaction rates which are (a) difficult to measure, and (b) may strongly influence the result (zero deficiency). If you want conclusions independent from reaction rates, then put W in “nonlinear”.

	advantage	disadvantage
<i>Blue</i>	stronger results	results may depend on W
<i>Green</i>	weaker results	no dependence on W

To get stronger results, need kernels of directed Laplacians, not (well)-known in the 70's.

**THE ZERO
DEFICIENCY
THEOREM**



*"I'm sorry, there's no such thing
as a chocolate deficiency."*

Some Definitions ...

Definition. The Laplacian deficiency is given by

$$\delta := \dim \text{Ker } SL_0^T - \dim \text{Ker } L_0^T$$

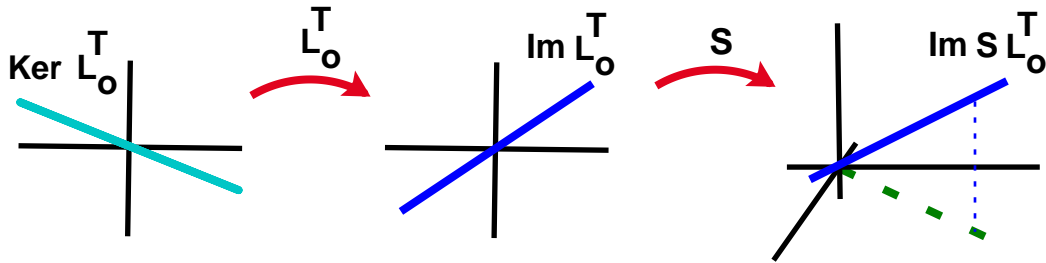


Figure: \dim of $\text{Im } L_0^T$ equals that of $\text{Im } SL_0^T$. So $\delta = 0$ and **None of the dynamics is hidden by S !**

Recall:

- (i)** Graph G is componentwise strongly connected (CSC) if each weak component is strongly connected (see DI).
- (ii)** The algebraic and geometric multiplicity of the eigenvalue 0 of L equals k , the number of reaches (see DII).
- (iii)** Left kernel of L is spanned by *row* vectors $\bar{\gamma}_i$ (see DII):

$$\left\{ \begin{array}{ll} \bar{\gamma}_m(j) > 0 & \text{if } j \in B_m \text{ (cabal)} \\ \bar{\gamma}_m(j) = 0 & \text{if } j \notin B_m \\ \sum_{j=1}^k \bar{\gamma}_m(j) = 1 \\ \{\bar{\gamma}_m\}_{m=1}^k \text{ are orthogonal} \end{array} \right.$$

Definition. (i) For x, y in \mathbb{R}^n : $x > y$ if true componentwise.

(ii) For $x > 0$ in \mathbb{R}^n , define $\text{Ln } x$ as $(\ln x_1, \dots, \ln x_n)$.

... and the Theorem

The theorem that initiated the mathematical study of CRNs was proved in 1972 [2]. We give a modern version due to [5].

Exercise: Recall that if $x > 0$, then $\text{Ln } \psi(x) = S^T \text{Ln } x$.

Zero Laplacian Deficiency Theorem. Suppose a CRN has $\delta = 0$. Then

$$\dot{x} = -S L_{\text{out}}^T \psi(x)$$

has a (strictly) pos. equil. \iff its graph is CSC.

In what follows, x denotes a vector in \mathbb{R}^v , a a real number, and $\mathbf{1}_S$ a vector in \mathbb{R}^v that is 1 on S and 0 else.

Exercise: Show that if $a > 0$ and $x > 0$, then

$$\text{Ln } ax = \ln a \cdot \mathbf{1} + \text{Ln } x$$

Lemma. The condition $\delta = 0$ is equivalent to

$$\text{Im } S^T + \text{Ker } L_o = \mathbb{R}^v$$

Proof. $\delta = 0$ is equivalent to $\text{Ker } S \cap \text{Im } L_o^T = \{0\}$.

Take orthogonal complement of both sides to get

$$(\text{Ker } S)^T + \text{Im } (L_o^T)^T = \mathbb{R}^v$$

The LHS equals $\text{Im } S^T + \text{Ker } L_o$ by linear algebra. **Done.**

Proof of \Rightarrow

Assume

$$\dot{x} = -SL_{\text{out}}^T \psi(x)$$

has pos. equil. x^* and prove CSC.

Existence of pos. equil. $x^* > 0$ shows that, since there is $x^* > 0$ with $\dot{x}^* = 0$,

$$\psi(x^*) > 0 \quad \text{such that} \quad SL_{\text{out}}^T \psi(x^*) = 0$$

No hidden dynamics (or $\delta = 0$) then gives

$$L_{\text{out}}^T \psi(x^*) = 0 \quad \text{or} \quad \psi(x^*)^T L_{\text{out}} = 0$$

By theorems on left kernels (see DII), we may therefore write

$$\psi(x^*)^T = \sum_{i=m}^k a_m \bar{\gamma}_m \quad \text{and} \quad \forall a_m > 0$$

But $\psi(x^*) > 0$ and γ_m are positive on cabals only. So every vertex is in a cabal. Therefore the graph is CSC.

Done.

Proof of \Leftarrow

Assume CSC, then show that

$$\exists x^* > 0 \text{ such that } \psi(x^*) = \sum_{i=1}^k a_i \bar{\gamma}_i^T \text{ and } \forall a_i > 0$$

Exercise: Use the two exercises on pg 22 to deduce that the **blue** equation can be rewritten as

$$S^T \text{Ln } x^* = \sum_{m=1}^k (\ln a_m) \mathbf{1}_{\mathbf{R}_m} + \text{Ln } \sum_{m=1}^k \bar{\gamma}_m^T.$$

where $\mathbf{1}_{\mathbf{R}_m}$ is the characteristic vector of the m th reach (component in this case).

Proof continued: Then re-arrange this as

$$\text{Ln } \sum_{m=1}^k \bar{\gamma}_m^T = S^T \text{Ln } x^* - \sum_{m=1}^k (\ln a_m) \mathbf{1}_{\mathbf{R}_m}$$

1st term of RHS ranges over $\text{Im } S^T$ and 2nd over $\text{Ker } L$.

This has a solution if

$$\text{Im } S^T + \text{Ker } L = \mathbb{R}^v.$$

Guaranteed by zero deficiency condition (use the Lemma).

Done.

Returning to the Example:

$$\begin{array}{ccc} v_1 & \xrightarrow{e_1} & v_2 \\ v_3 & \xrightarrow{e_2} & v_4 \end{array}$$

This graph has two weak components, neither of which is SC.

$$S = \begin{pmatrix} 2 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 0 & 2 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \quad \text{and} \quad L_o^T = \begin{pmatrix} k_1 & 0 & 0 & 0 \\ -k_1 & 0 & 0 & 0 \\ 0 & 0 & k_2 & 0 \\ 0 & 0 & -k_2 & 0 \end{pmatrix}$$

Exercise: Find the span of $\text{Im } L_o^T$ and of $\text{Ker } S$.

Conclude from the exercise that $\delta = 0$.

Conclude from 0-def thm that there is no strictly pos equil.

Confirm that conclusion from the equations:

$$\begin{aligned} \dot{x}_1 &= -2k_1 x_1^2 x_2 \\ \dot{x}_2 &= -k_1 x_1^2 x_2 - k_2 x_2 x_4 \\ \dot{x}_3 &= 2k_1 x_1^2 x_2 \\ \dot{x}_4 &= -k_2 x_2 x_4 \\ \dot{x}_5 &= k_2 x_2 x_4 \end{aligned}$$

FURTHER DEVELOPMENTS



**Sorry Professor, you're right:
I DID skip a line of the instructions...**

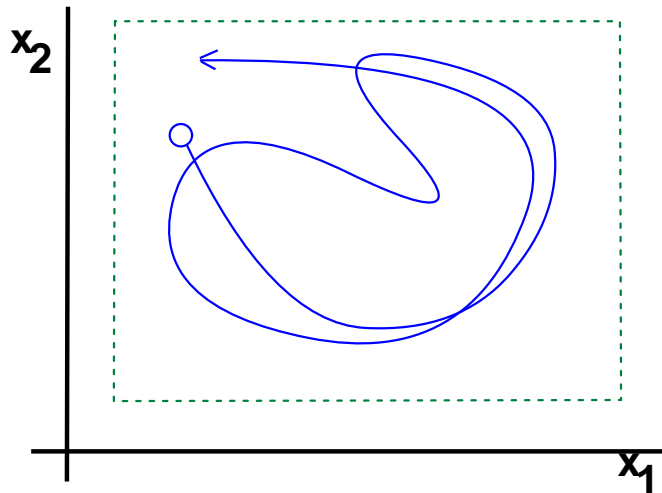
Bounded Orbits

Theorem [5]. Suppose $\delta = \mathbf{0}$. Then

$$\dot{x} = -S L_{\text{out}}^T \psi(x)$$

has pos. orbit $x(t)$ with $\text{Ln } x(t)$ bdd \iff graph is CSC.

Note: \Leftarrow follows from 0-def. But \Rightarrow strengthens it.



The 0-def thm says: CSC implies existence of equilibrium. So:

Corollary. A 0-def system with an orbit $x(t)$ whose Log is bounded (see figure) must have a fixed point.

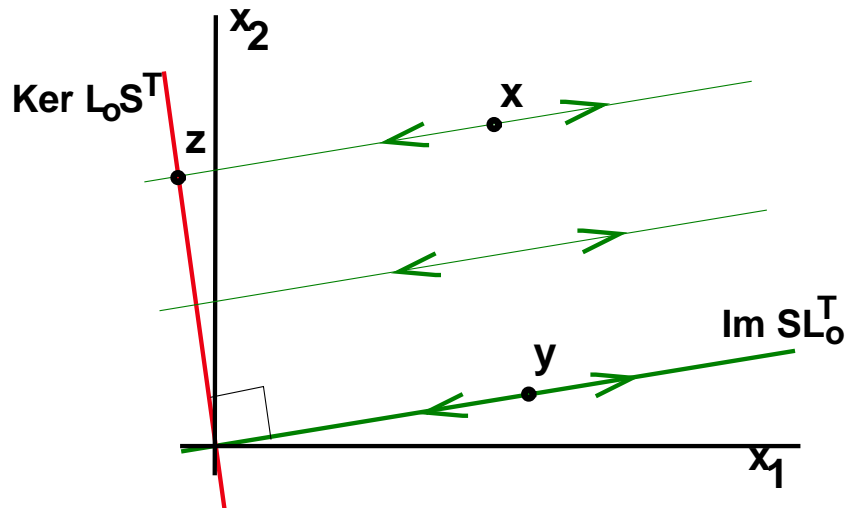
Constants of the Motion and Stability

Exercise: Show that $(\text{Im } A)^\perp = \text{Ker } A^T$.

Thus the orbit $x(t)$ of

$$\dot{x} = -SL_{\text{out}}^T \psi(x)$$

\dot{x} is parallel to $\text{Im } SL_o^T$ and $x(t) = z + y(t)$, z constant. z is the orthogonal proj onto $\text{Ker } L_o S^T$.



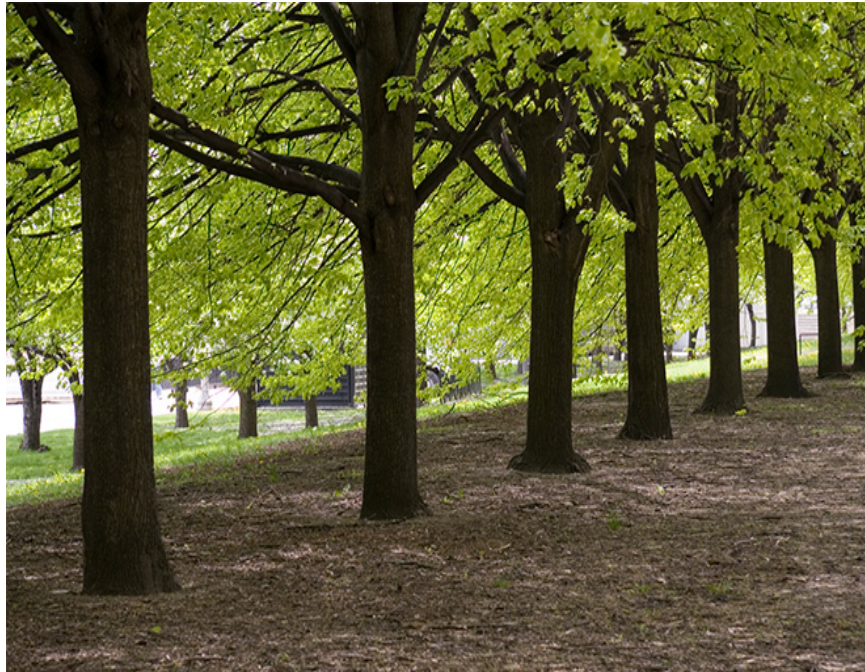
Theorem [5]. Suppose $\delta = 0$ and CSC. Then:

- (i) For every $z \in \text{Ker } LS^T$, there is a unique $y \in \text{Im } SL^T$ such that $y + z$ is a positive equilibrium.
- (ii) The ω -limit set of any positive initial condition either equals that equilibrium or is a bounded set contained in the boundary of the positive orthant.

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**FORMULATION
OF THE
MATRIX TREE
THEOREM**

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Lots of Trees

Definition: For the purpose of this section, we write:

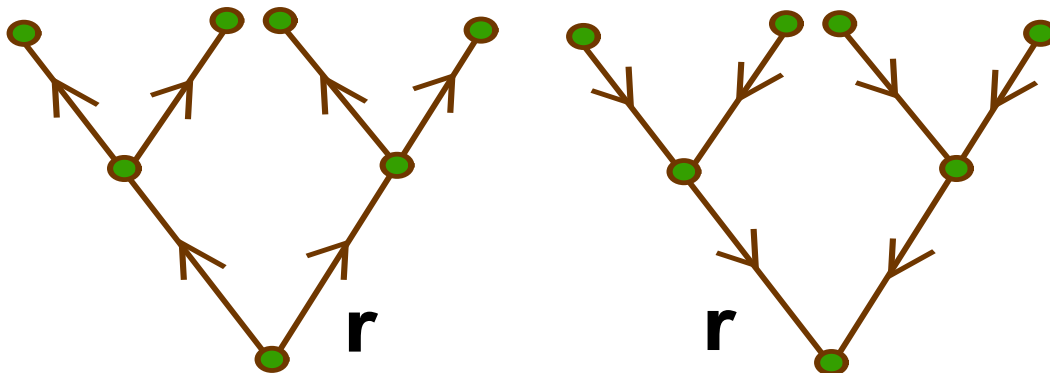
$$\begin{aligned}
 L_{\text{in}} &= (EW)(E^T - B^T) \\
 L_{\text{out}} &= (-BW)(E^T - B^T) \\
 \underline{L} &= (EW - BW)(E^T - B^T) \\
 &= (E - B)W(E^T - B^T)
 \end{aligned}$$

Definition: A spanning **out**-tree rooted at vertex r (**SOTR**) is a graph such that

- if $i \neq r$, then **in**-degree at i equals 1.
- **in**-degree at r equals 0.
- no directed cycles.

For a **SITR**: swap “out” and “in”.

Figure: Left: **out**-tree rooted at r , and right: **in**-tree.



Definition: A spanning **undirected** tree rooted at r (**SUTR**) is a connected graph with no cycles. (No loose vertices.)

And To Each Their Tree

$$\begin{aligned}L_{\text{in}} &= (EW)(E^T - B^T) \\L_{\text{out}} &= (-BW)(E^T - B^T) \\ \underline{L} &= (EW - BW)(E^T - B^T)\end{aligned}$$

$$(EW)_{ij} = \sum_k E_{ik} W_{kj}$$

So the effect of the diagonal matrix W is to multiply the i th edge (column) by the i th entry W_{ii} .

Definition: The **weight** $W(T)$ of a tree T is the product of the weights of all its edges. Allow arbitrary (positive) weights. The weighted adjacency matrix is denoted by S and the diagonal row-sum matrix of S is denoted by D .

Definition: For a Laplacian L , let \mathcal{T}_r be the **appropriate** set of spanning trees rooted at r . By this we mean:

- For L_{in} , it is the SOTR's
- For L_{out} , it is the SITR's
- For \underline{L} , it is the SUTR's.

Matrix Tree Theorems

Definition: Assume G has n vertices. Let I_r be the set V of all vertices **except** r .

Theorem 2 (Matrix Tree): L a Laplacian. Then

$$q_r := \det L[I_r, I_r] = \sum_{T_r \in \mathcal{T}_r} W(T_r)$$

Observation 1: If G has $k > 1$ reaches, then no SORTs. DII Thm 9: L has eval 0 with mult. $k > 1$. Reducing L by 1 column and row will give $\det L[I_r, I_r] = 0$.

Exercise: Show that for a digraph G with one reach, if r is not in a cabal, then $\det L[I_r, I_r] = 0$.

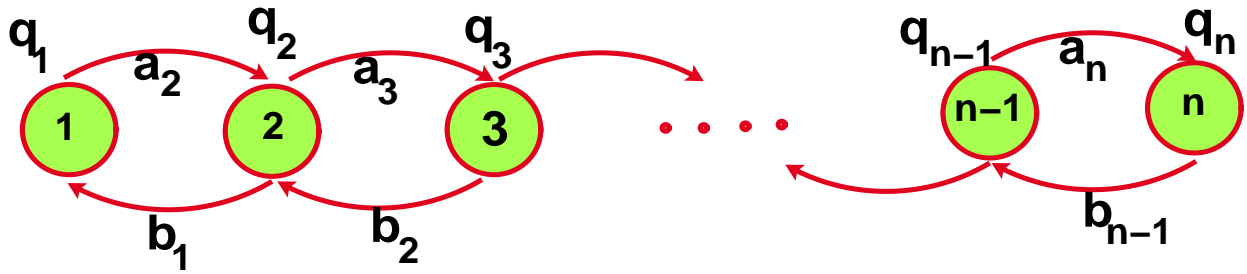
The proofs of the cases where $L = L_{\text{in}}$ or $L = L_{\text{out}}$ are almost identical (just swap “in” and “out”). In the undirected case: reaches are connected components.

Theorem 3: Furthermore

$$\sum_r q_r L_{ri} = 0$$

Observation 2: Thus the **weight** of rooted trees at vertex r has a probabilistic interpretation. (Gives stationary probability measure under rw.)

Exercises Using Path Graph



Exercise: For the graph above write out L_{in} .

Exercise: Let q_k the weight of out-trees rooted in vertex k . Show that $q_k = \prod_{k+1}^n a_i \prod_{i=1}^{k-1} b_i$.

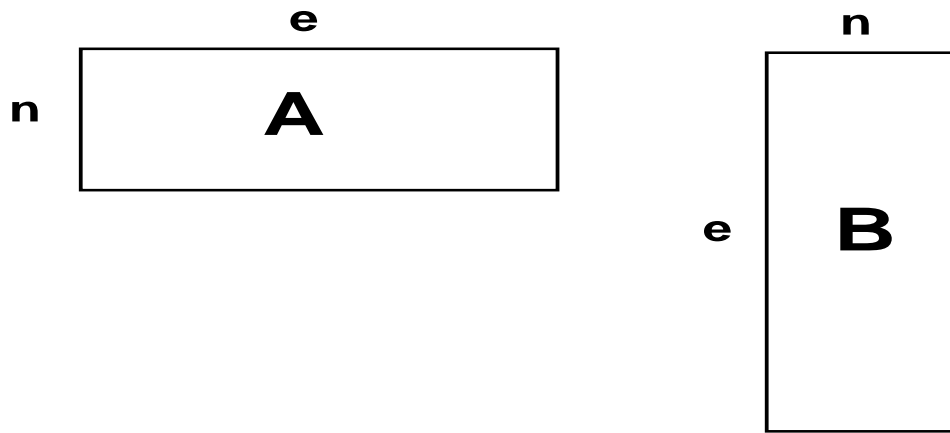
Denote by q the row-vector (q_1, q_2, \dots, q_n) .

Exercise: Show that $qL_{\text{in}} = 0$.

Exercise: Repeat exercises on this page, but now for L_{out} and \underline{L} .

**PROOF OF
MATRIX TREE
FOR L_{in}**

First Use Cauchy-Binet



Definition (DI): I (K) subset of the row (column) labels of matrix A . $A[I, K]$ consists of the entries of A in $I \times K$.

Exercise: $L = AB$ where A and B matrices as depicted above. Show that matrix multiplication implies

$$L[I, J] = A[I, \text{all}]B[\text{all}, J]$$

Now let $|I| = |J| = k$. By Cauchy-Binet (Thm 3 of DI):

$$\det((AB)[I, J]) = \sum_{K, |K|=k} \det(A[I, K]) \det(B[K, J])$$

Since $L_{\text{in}} = (EW)(E^T - B^T)$, we have

Proposition: $I_r := V \setminus \{r\}$. Then $\det(L_{\text{in}}[I_r, I_r])$ equals

$$\sum_{K, |K|=n-1} \det((EW)[I_r, K]) \det((E^T - B^T)[K, I_r])$$

Assume K Not a Tree

Recall: **SOTR** is a graph such that

1. if $i \neq r$, then **in-degree** at i equals **1**.
2. **in-degree** at r equals **0**.
3. **no directed cycles**.

$$\det(L_{\text{in}}[I_r, I_r]) = \sum_K \det((EW)[I_r, K]) \det((E^T - B^T)[K, I_r])$$

In RHS, each choice of K selects $n - 1$ edges.

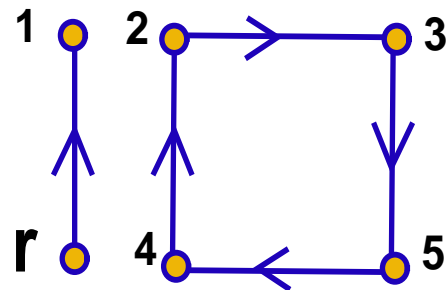
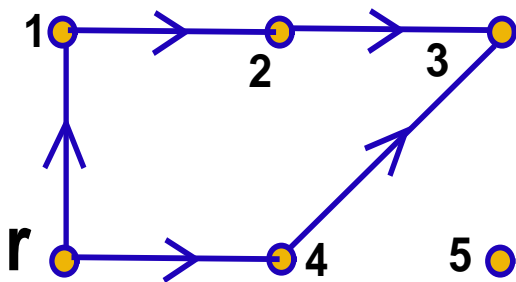
If the $n - 1$ edges K do not form a SOTR:

Fail 1 $\Rightarrow \exists i \neq r$ with in-degree 0 $\Rightarrow E$ has zero row, or

Fail 2 \Rightarrow in-degree at r not 0 \Rightarrow same as fail 1, or

Fail 3 $\Rightarrow \partial(\text{cycle}) = 0 \Rightarrow \ker(E^T - B^T)$ has $\dim > 0$.

Example w. 6 vertices and 5 edges: Left: column 5 of



$E[I_r, K]$ is 0. Right: $(E^T - B^T)[\{2, 3, 4, 5\}, \{2, 3, 4, 5\}]$ has row sum 0.

Total contribution: zero!

Assume K a Tree

If the $n - 1$ edges of K do form a SOTR:

Relabel vertices and edges so that:

1. If $j > i$, then path from $r \rightsquigarrow i$ does not pass through j .
2. And then so that edge i ends in vertex i .

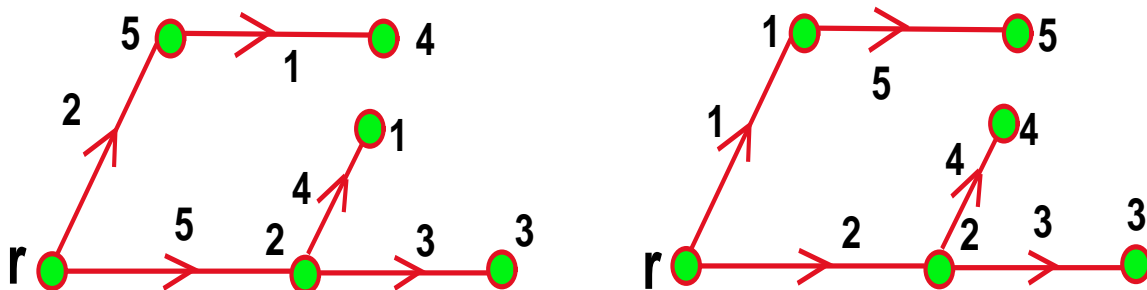
For each K , same permutations are done in two factors:

$$\sum_{K, |K|=n-1} \det((EW)[I_r, K]) \det((E^T - B^T)[K, I_r])$$

Thus the permutations have no net effect: $(-1)^{\text{even}}$!

Result: $E[I_r, K]$ is the identity, and $B[I_r, K]$ is upper tridiag with 0 on diag.

Example of SOTR w. 6 vertices and 5 edges: Left: Before



permutations. Right: After.

Total contribution: The weight of the tree!

Exercise: Repeat proof for L_{out} (trivial) and \underline{L} (needs minor adaptation).

TREES,
UNICYCLES,
PROBABILITY



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Lots of Unicycles, and to Each ...

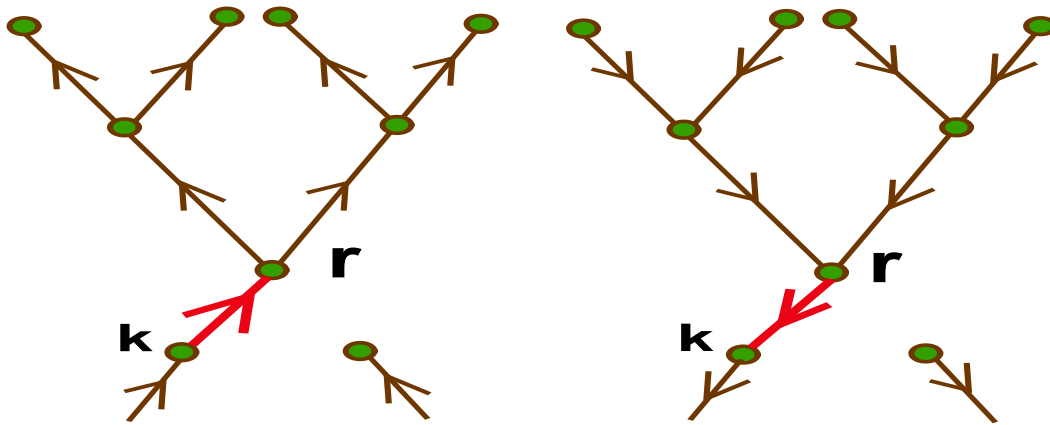
Definition: An **augmented** spanning **out**-tree rooted at vertex r (**ASOTR**) is a

SOTR plus 1 extra edge $k \rightarrow r$ such that $(L_{\text{in}})_{rk} > 0$.

Similarly, an **ASITR** is a

SITR plus 1 extra edge $r \rightarrow k$ such that $(L_{\text{out}})_{rk} > 0$.

Left: Augmented **out**-tree. Right: Augmented **in**-tree.



Definition: An augm. spanning undirected tree rooted at r (**ASUTR**) is a SUTR with 1 extra edge from r to a neighbor.

Remark: These graphs contain **1 cycle!** They are most commonly called **cycle-rooted trees** or **unicycles**.

Definition: For a Laplacian L , let \mathcal{A}_r be the **appropriate** set of augm. spanning trees rooted at r . By this we mean:

- For L_{in} , it is the ASOTR's
- For L_{out} , it is the ASITR's
- For \underline{L} , it is the ASUTR's.

Counting Unicycles at Vertex r

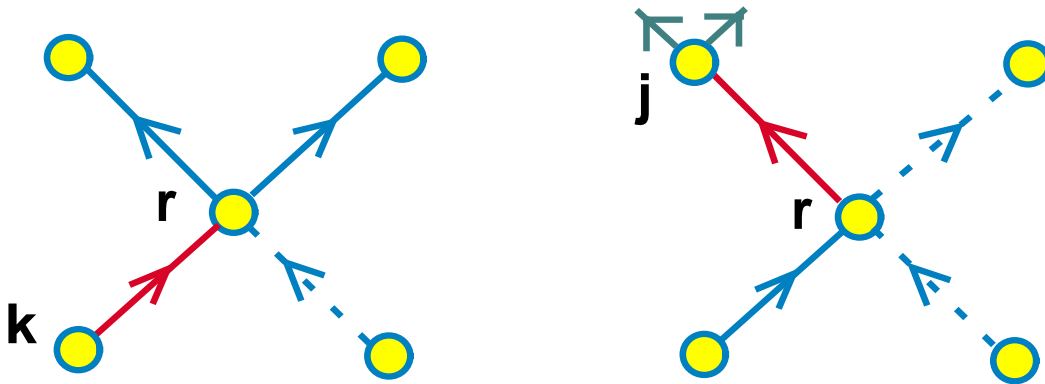
Exercise: Show that a unicycle contains exactly 1 cycle. (*Hint: contract along the spanning tree. The cycles are the remaining edges.*)

Two ways to compute the weight of the L_{in} -appropriate r -rooted unicycles (ASOTR's) for a given graph G (see figure).

RECALL: S is the weighted (by W) adjacency matrix. The diagonal row-sum matrix is D .

Left(1): To SOTR at r , add edge from *parent* k of r to r .

Right(2): To SORT at *child* j of r , add edge from r to j .



Total weight of unicycles rooted at r is denoted by u_r .

$$\text{From 1: } \mathbf{u}_r = \sum_{\mathbf{k}} \mathbf{q}_r \mathbf{S}_{r\mathbf{k}} = \mathbf{q}_r \mathbf{D}_{rr}$$

(Proof: The row-sum of S is given by D .)

$$\text{From 2: } \mathbf{u}_r = \sum_{\mathbf{j}} \mathbf{q}_j \mathbf{S}_{j\mathbf{r}}$$

Proof of Theorem 3

EASY ! Equate the two expressions:

$$0 = q_r D_{rr} - \sum_j q_j S_{jr} = [q(D - S)]_r = [qL_{\text{in}}]_r$$

which proves Thm 3 for L_{in} .

DONE!

Remark: If S is a rw walk matrix, then D is identity and q is the stationary probability measure.

Exercise: Prove Theorem 3 for L_{out} and \underline{L} .

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- [1] P. De Leenheer, *An Elementary Proof of a Matrix Tree Theorem for Directed Graphs*, <https://arxiv.org/abs/1904.12221>.
- [2] M. Feinberg. *Complex balancing in general kinetic systems*, **Archive for Rational Mechanics and Analysis**, 49(3):187–194, 1972.
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- [5] J. J. P. Veerman, T. Whalen-Wagner, E. Kummel *Chemical Reaction Networks in a Laplacian Framework*, **Chaos, Solitons, and Fractals**, accepted.