

Analysis of MPI Algorithms via Zeta Functions

Pascal O. Vontobel

Talk at CUHK, May 13, 2014

(Based on joint work with Henry D. Pfister, TAMU.)

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Theorem by Yedidia et al.
on fixed points of the SPA

EXIT charts
area theorem

linear programming
relaxation

Bethe free energy
and its pseudo-dual

density
evolution

graph
zeta
function

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We are looking for a *unifying perspective* to these topics.

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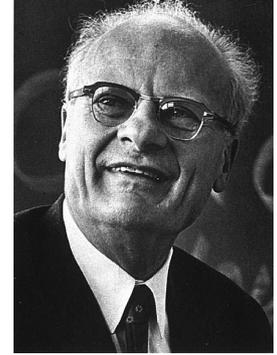
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Hans Bethe

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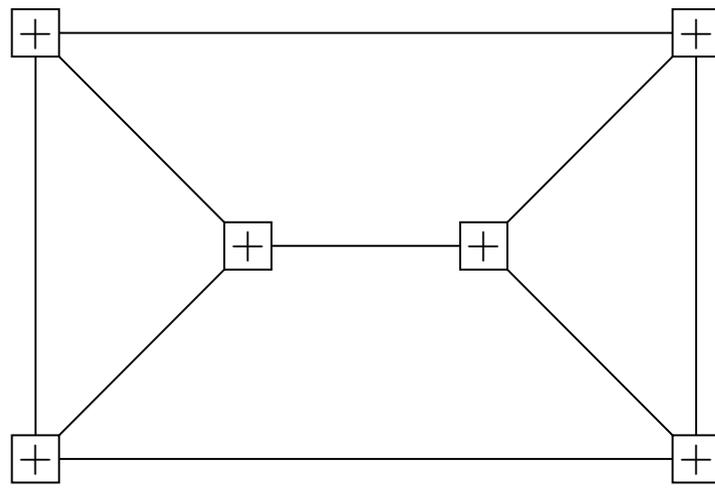
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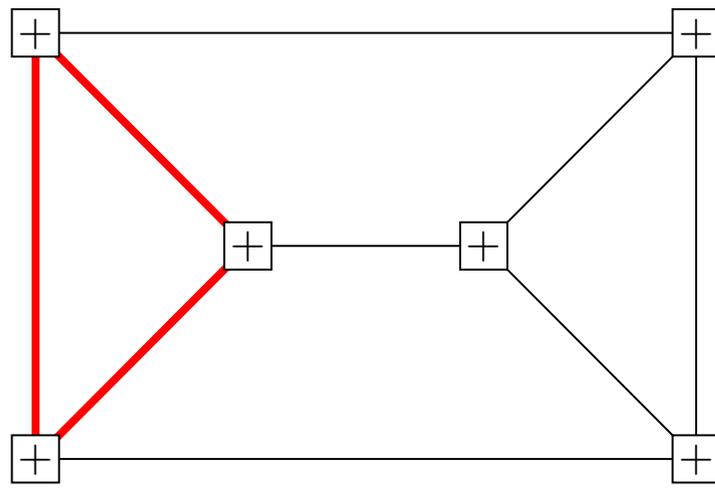
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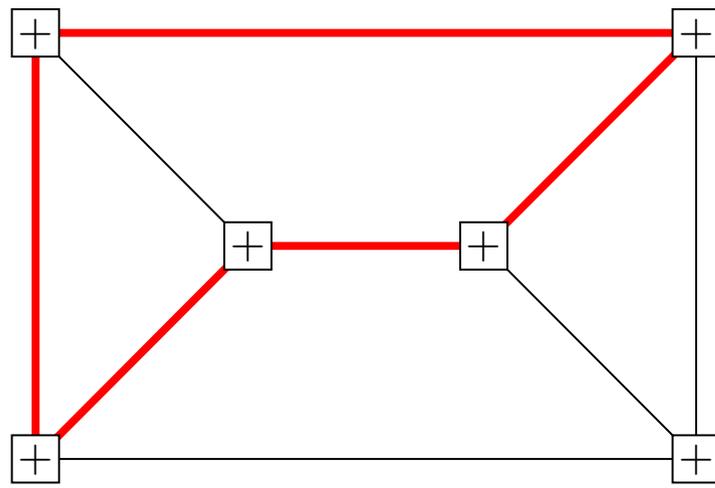
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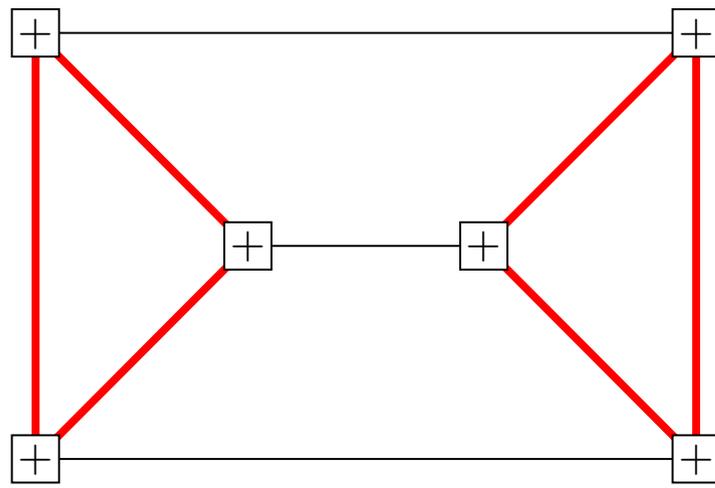
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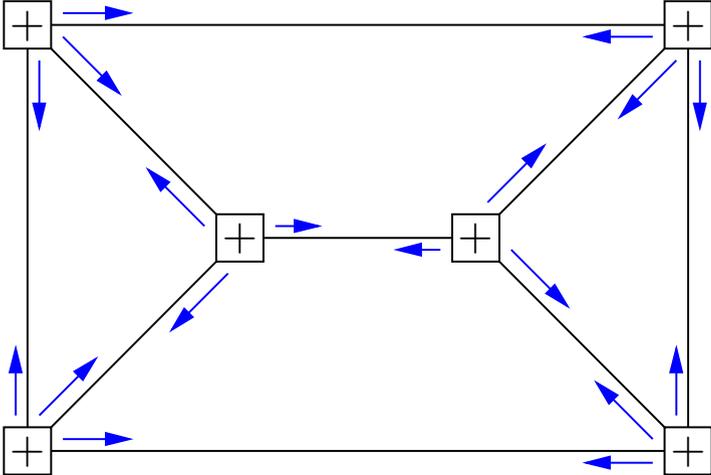
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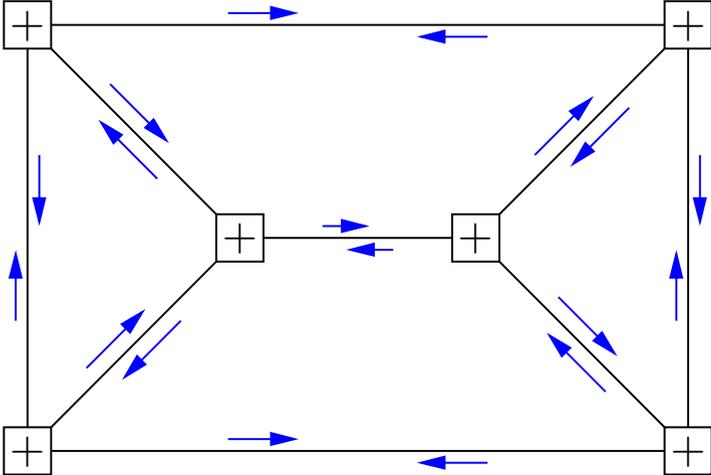


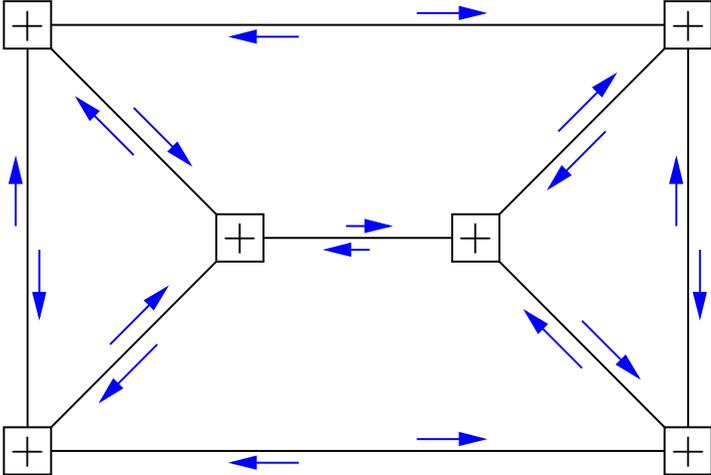


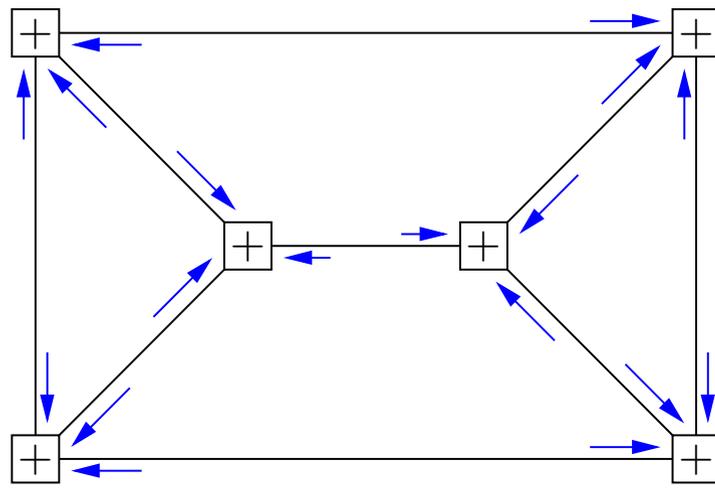


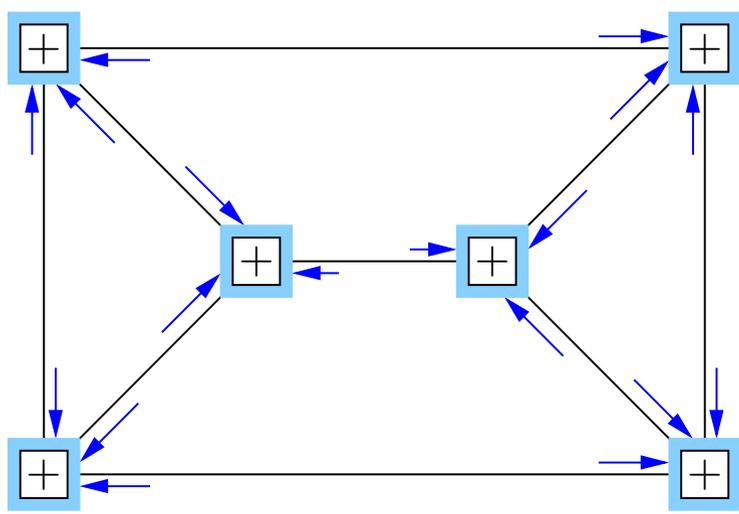


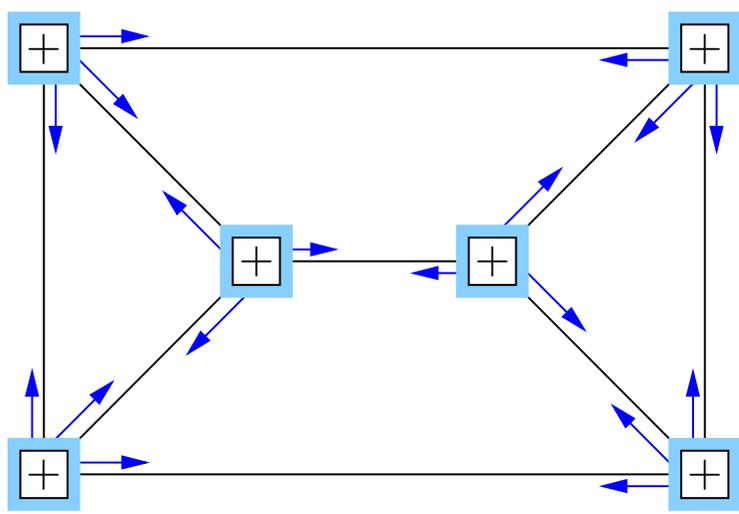


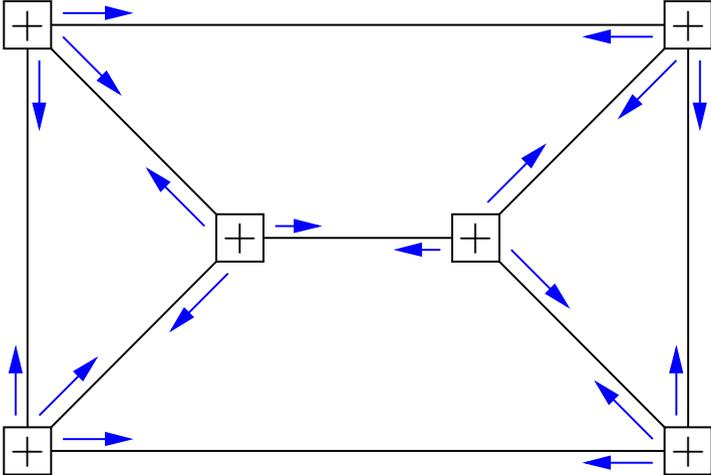


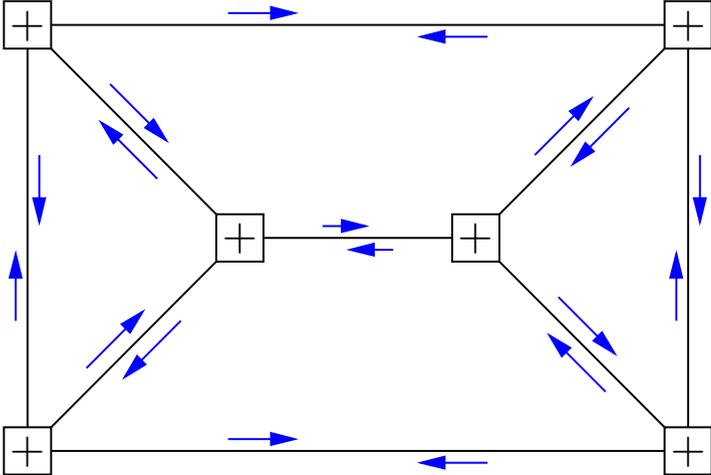


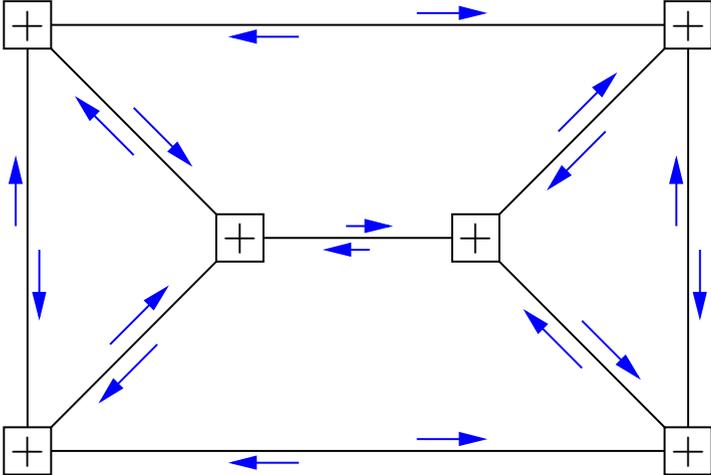


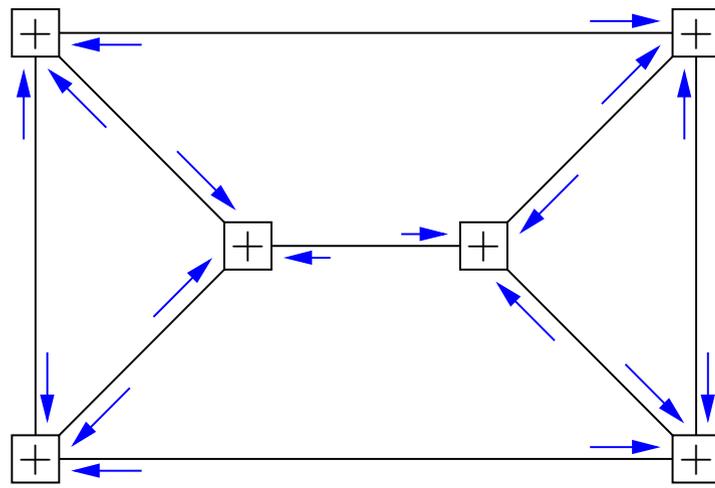


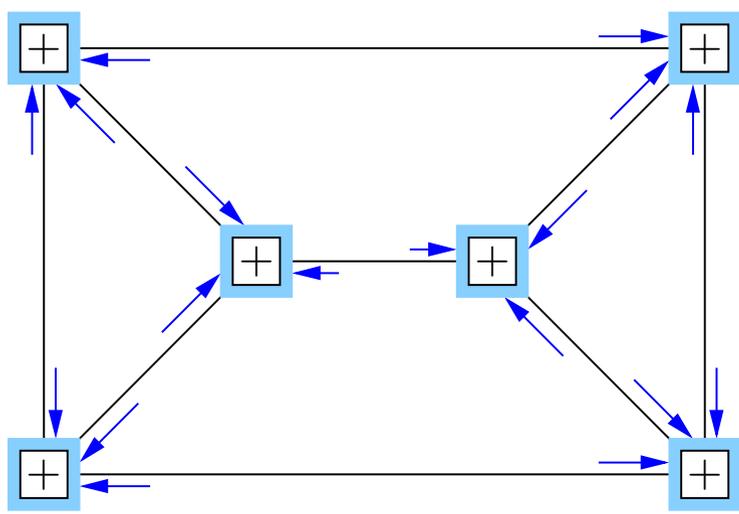


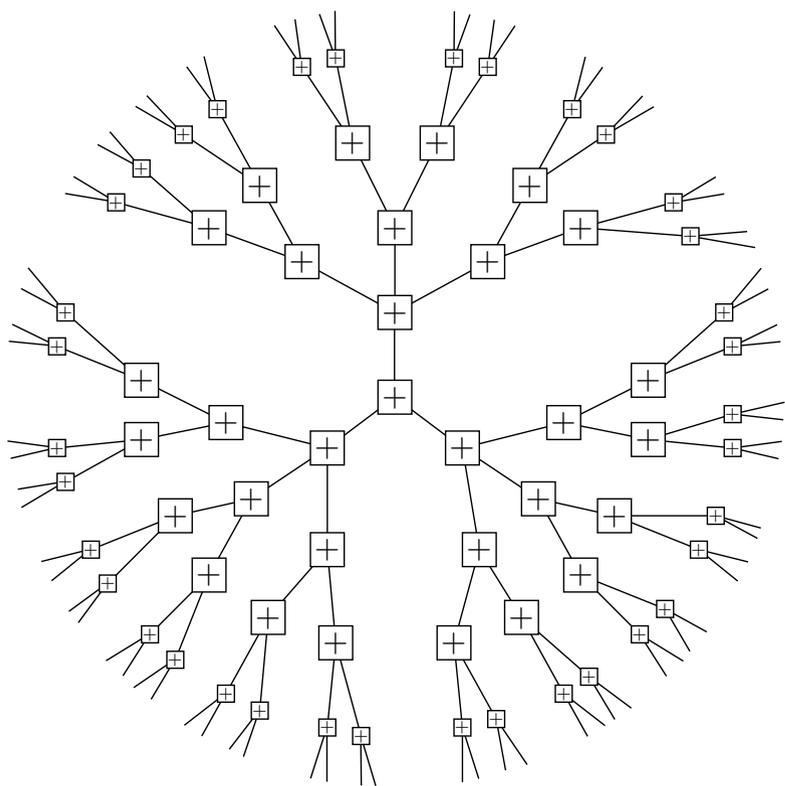
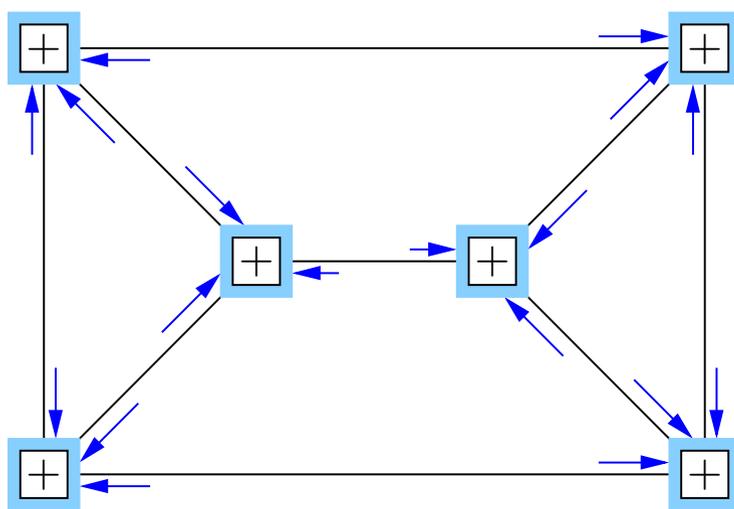


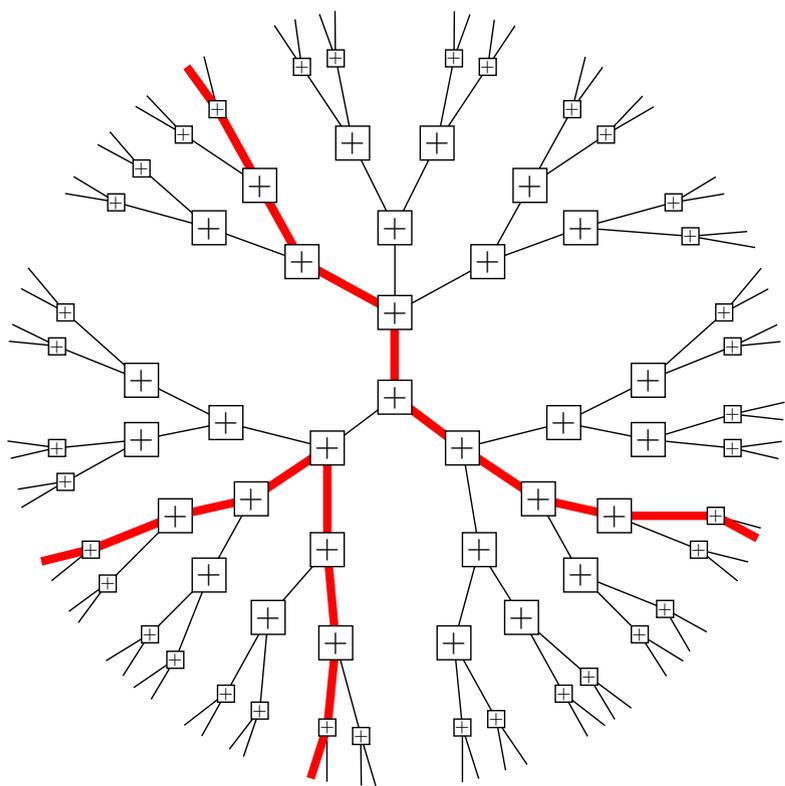
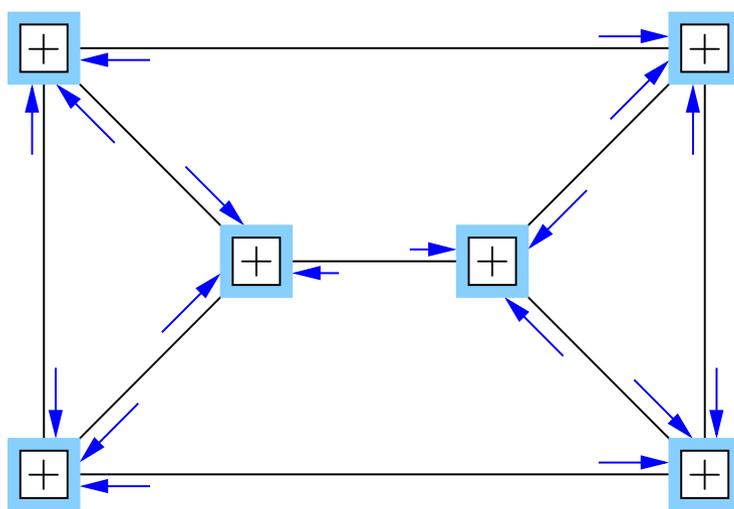


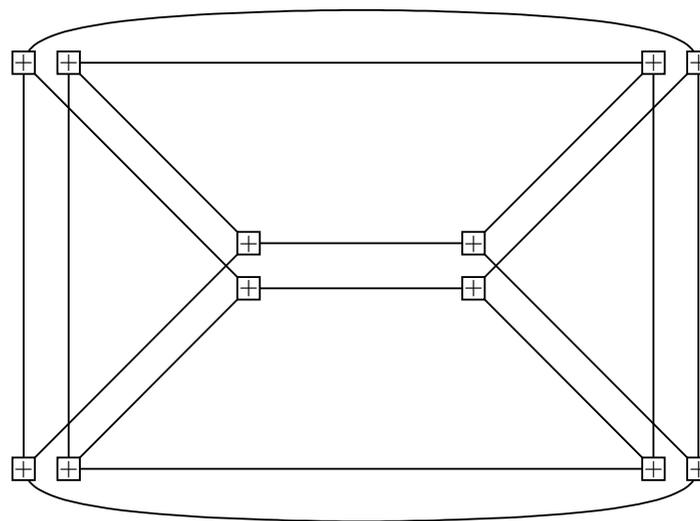
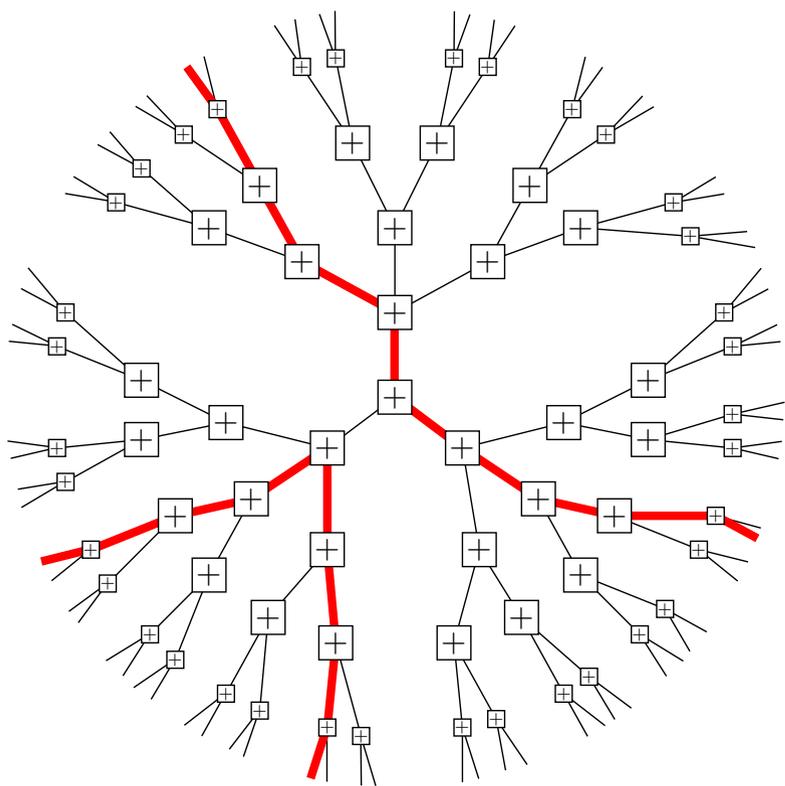
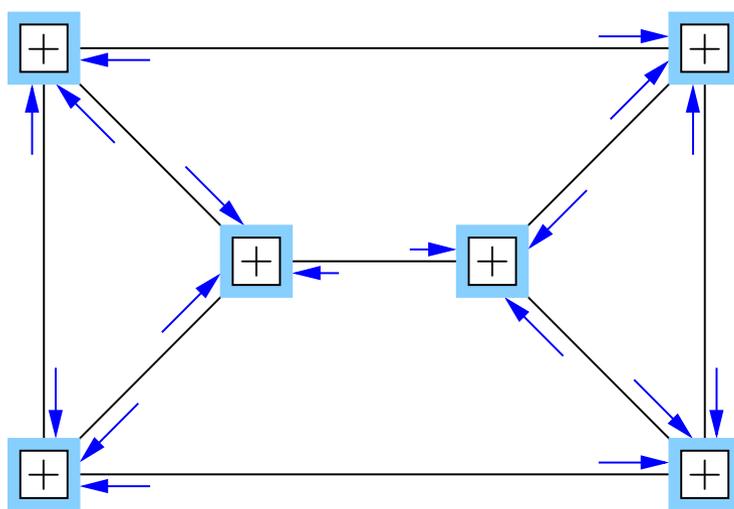


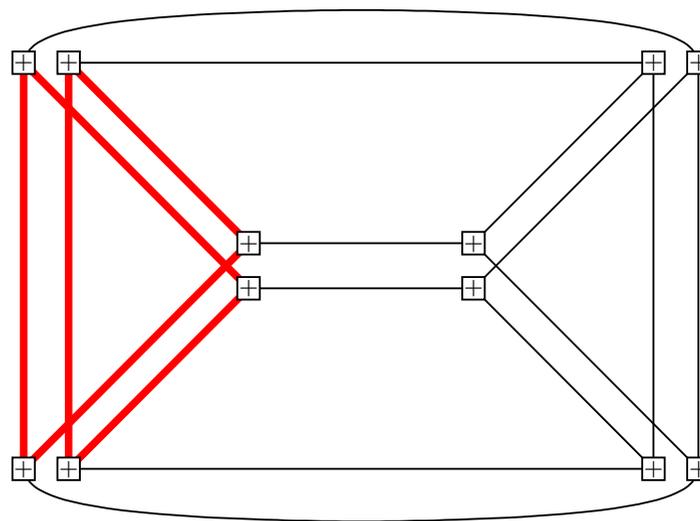
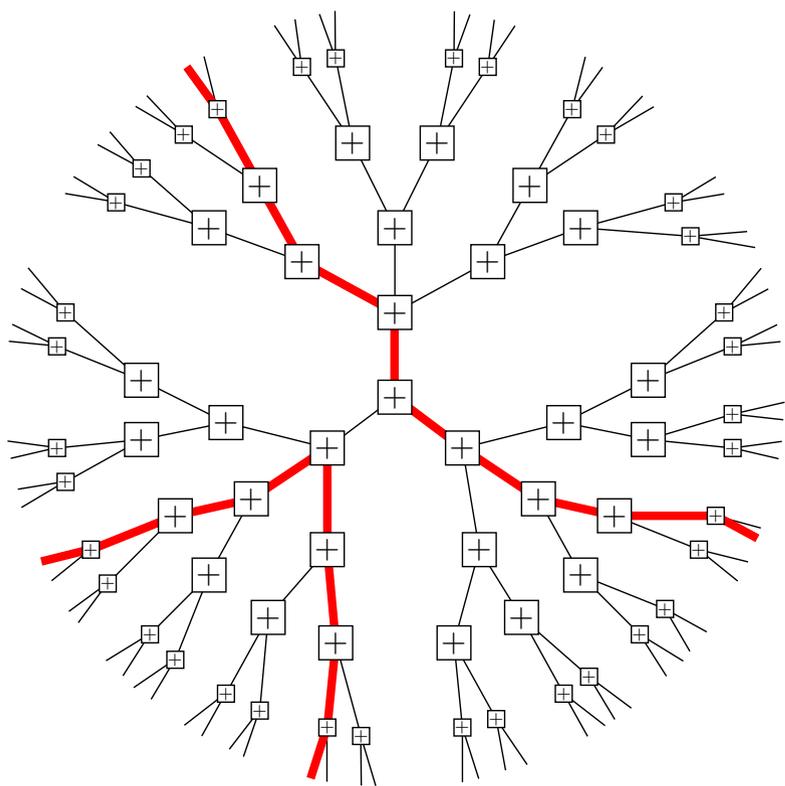
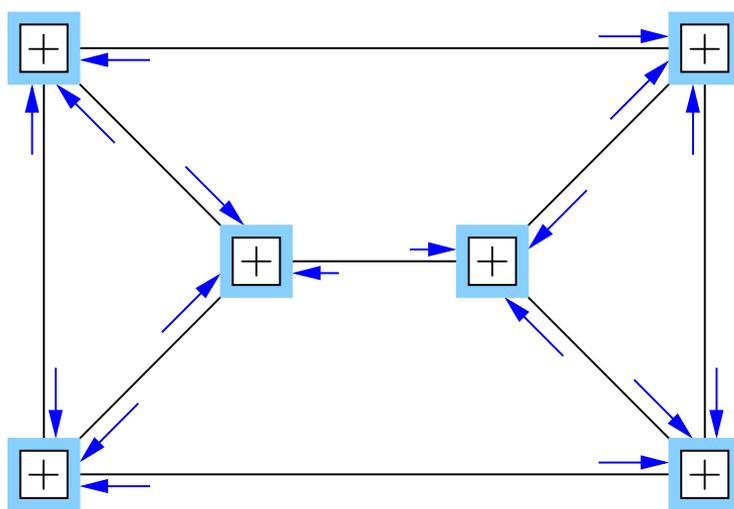


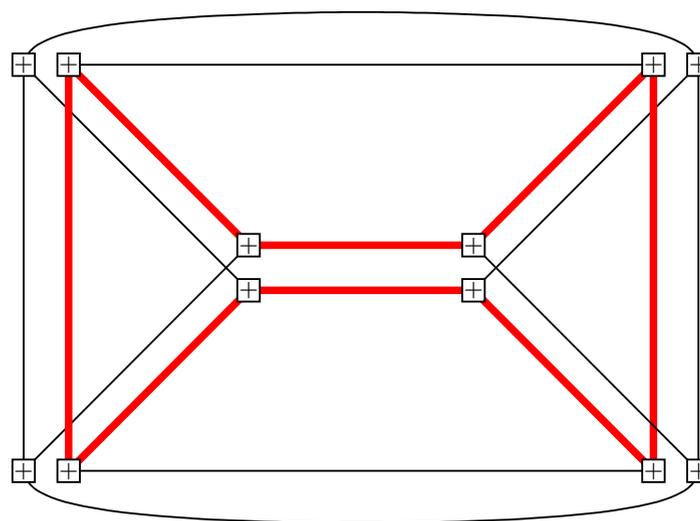
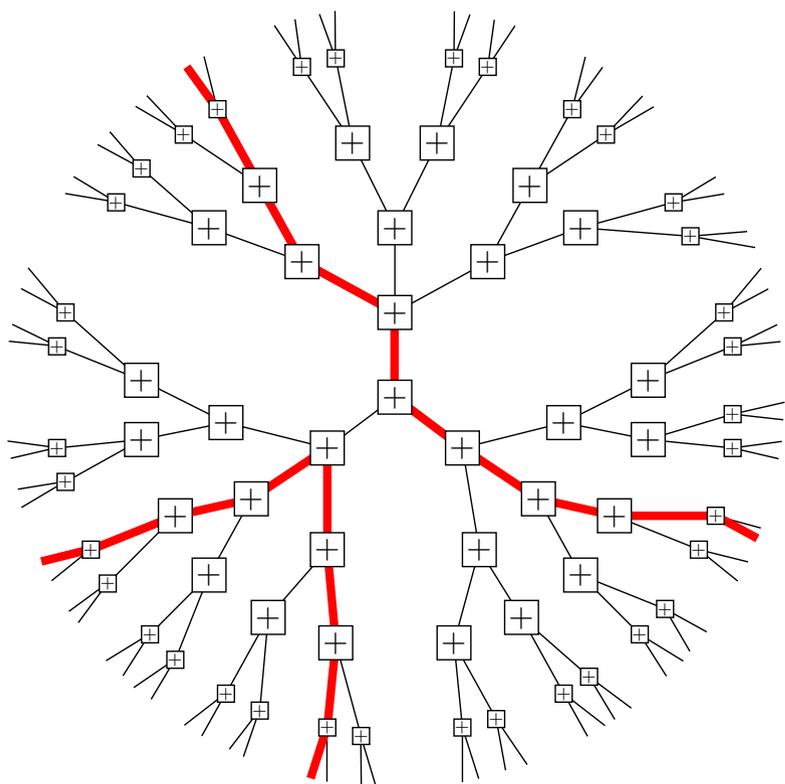
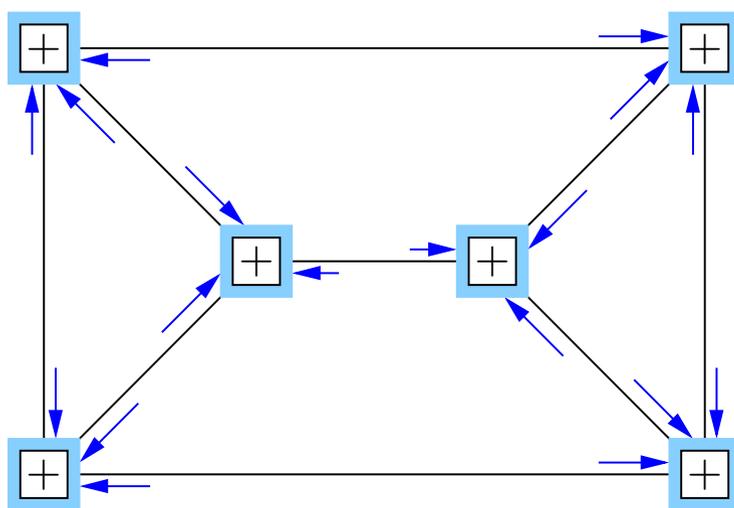


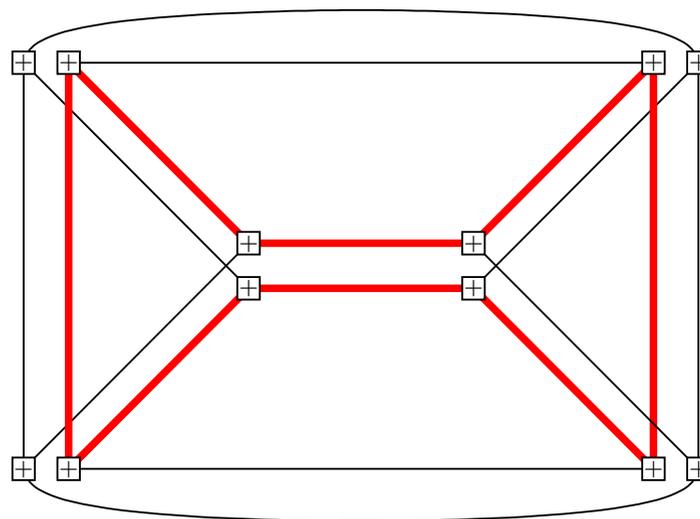
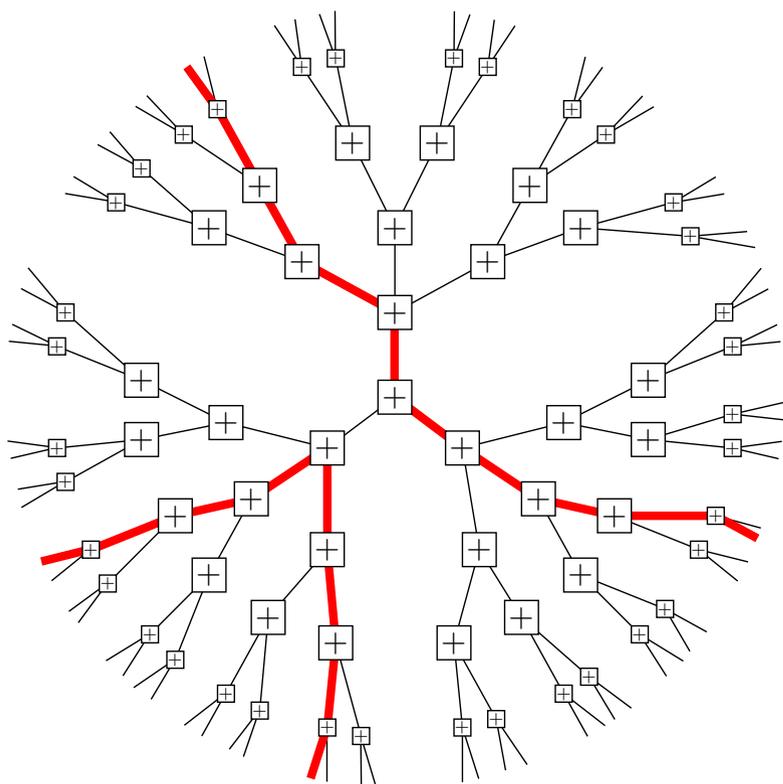
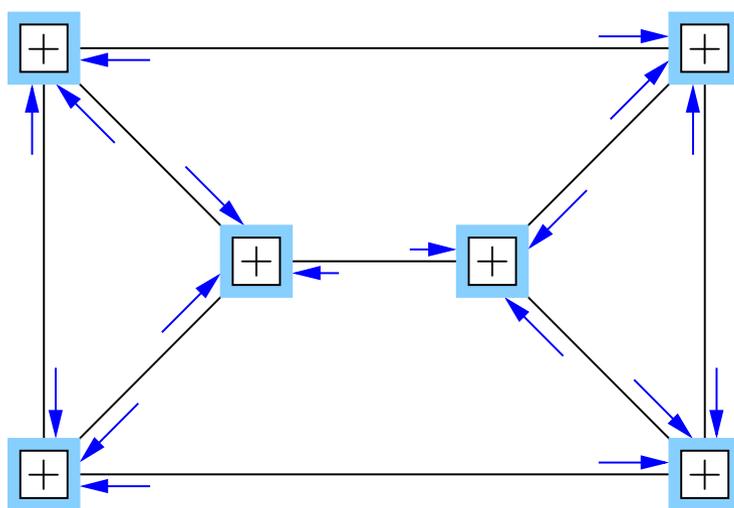




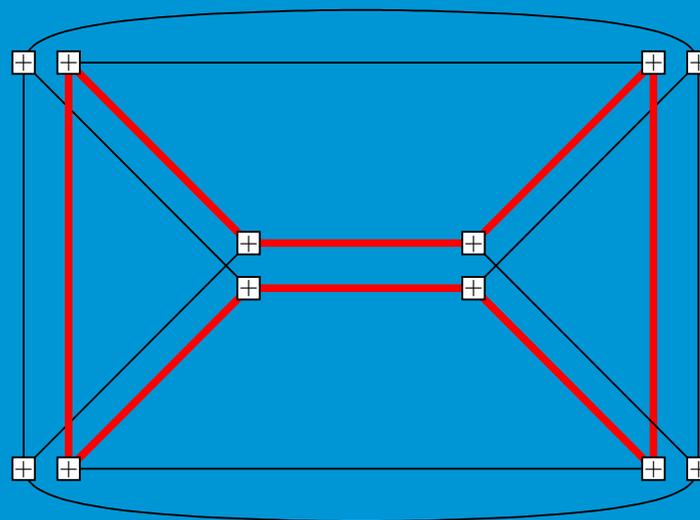
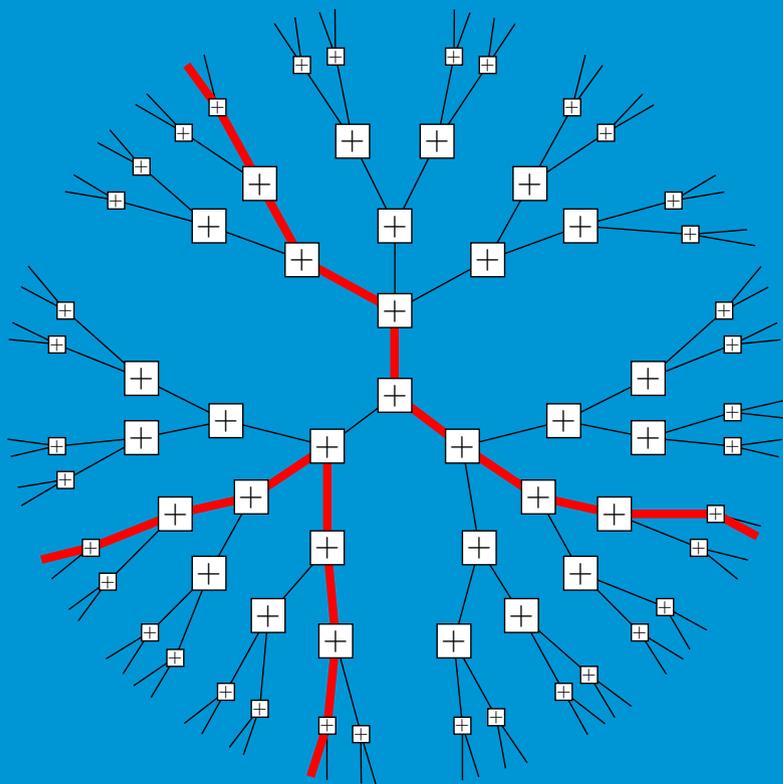
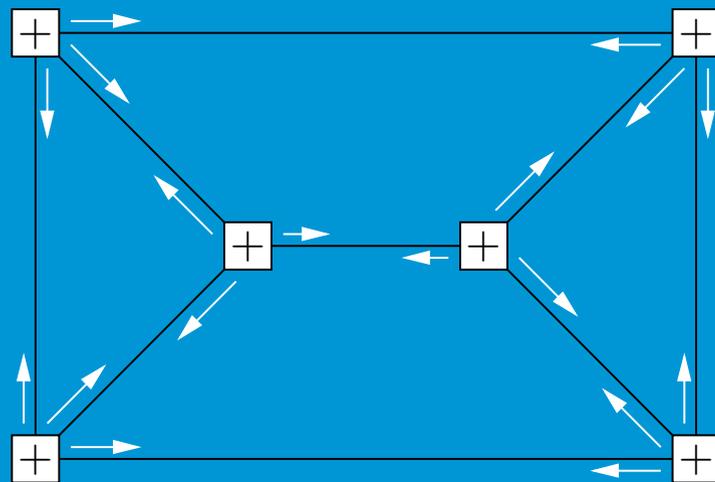






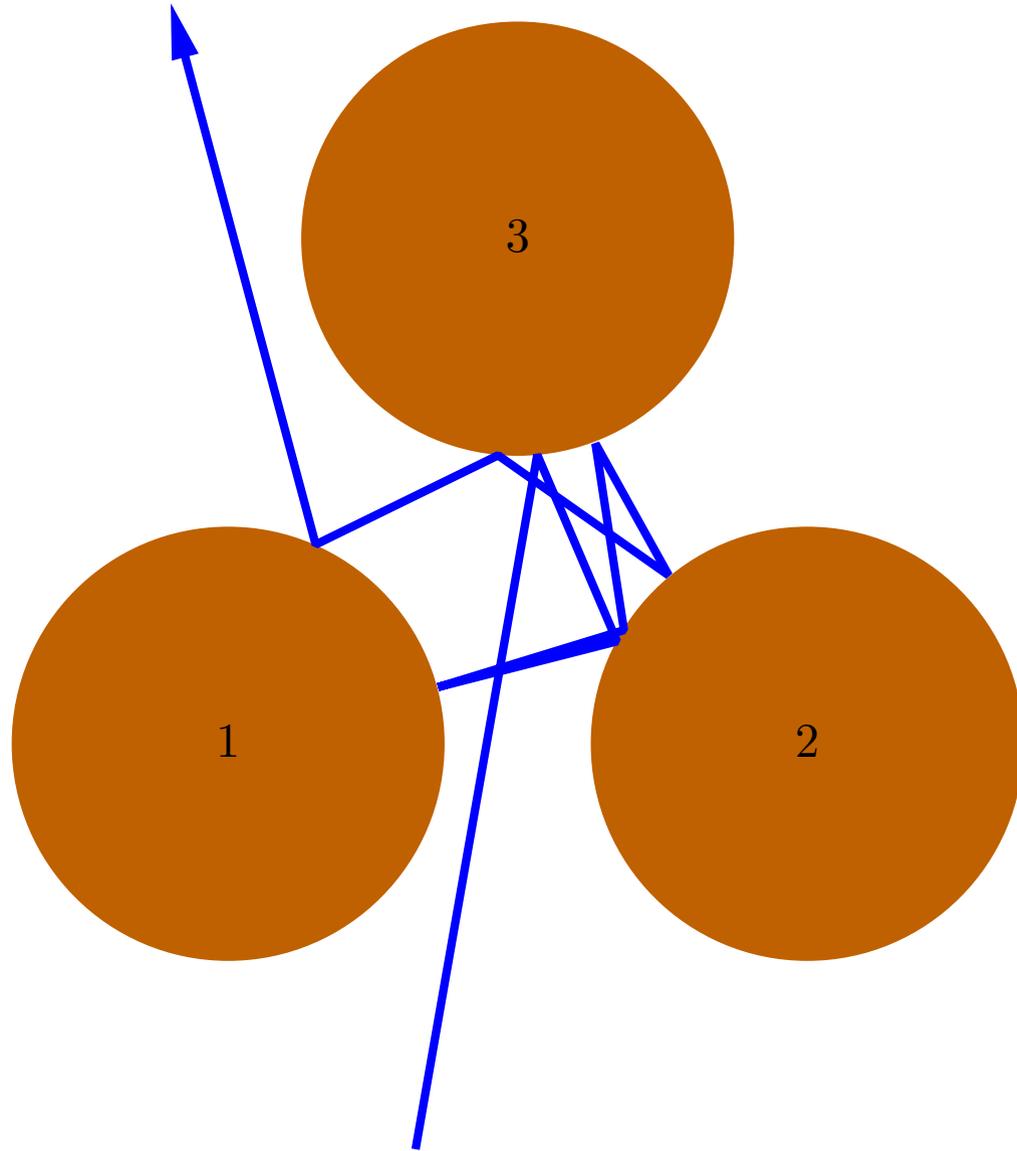


$$\zeta(\mathbf{V}_1, \dots, \mathbf{V}_n) = \sum_{\mathbf{k}} \zeta_{\mathbf{k}} \mathbf{V}^{\mathbf{k}} = \prod_{[\Gamma]} \frac{1}{1 - g(\Gamma, \mathbf{V})}$$

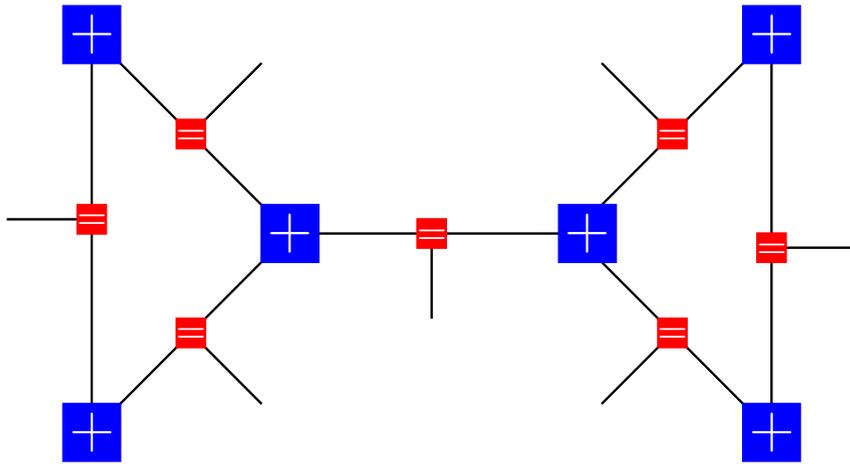


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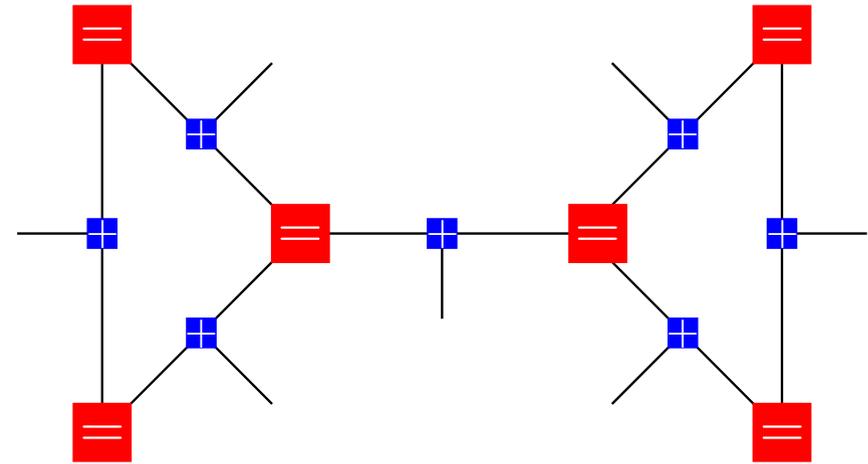
Pinball



Cycle Code NFG –vs– Community Det. NFG

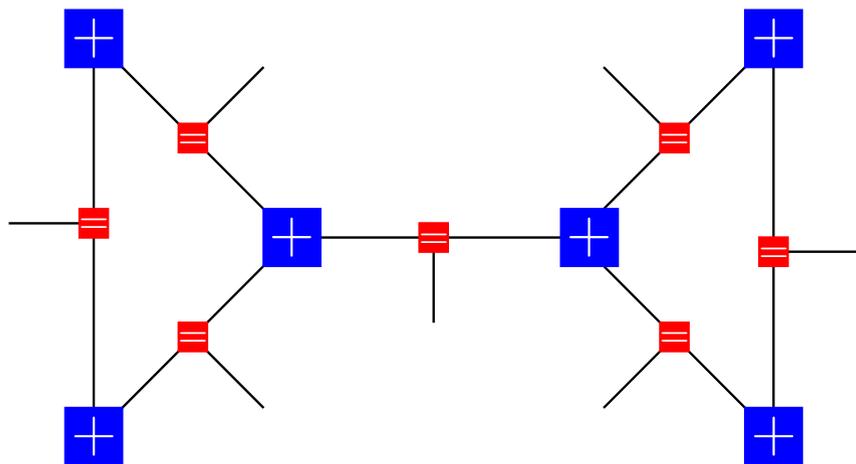


cycle code
normal factor graph

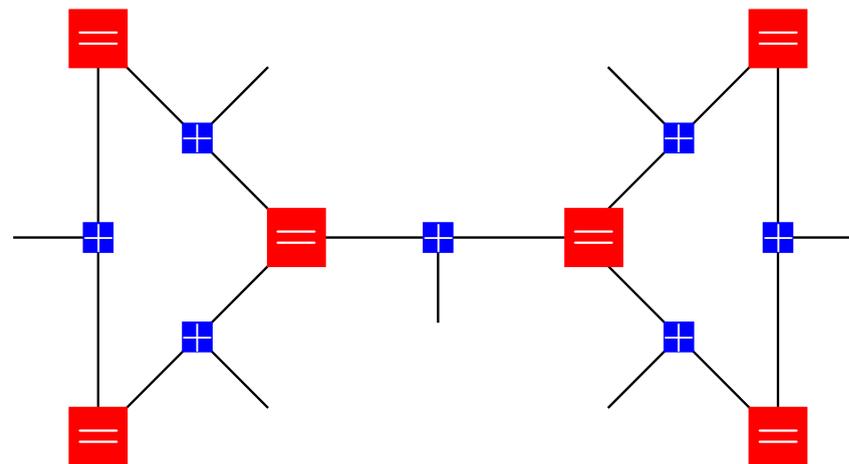


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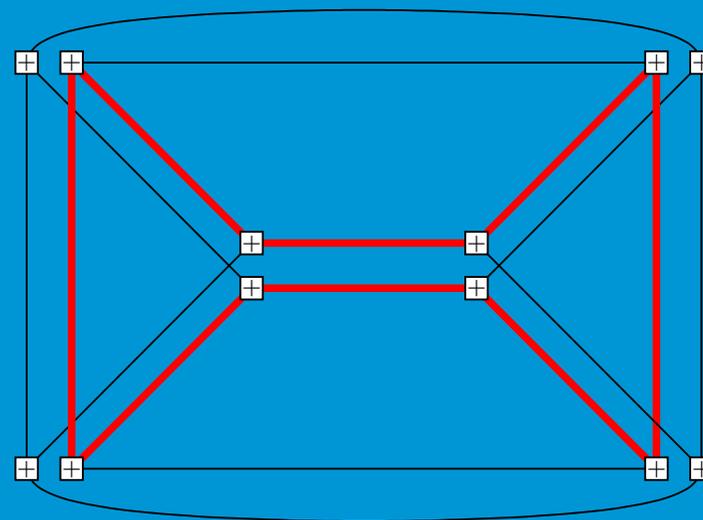
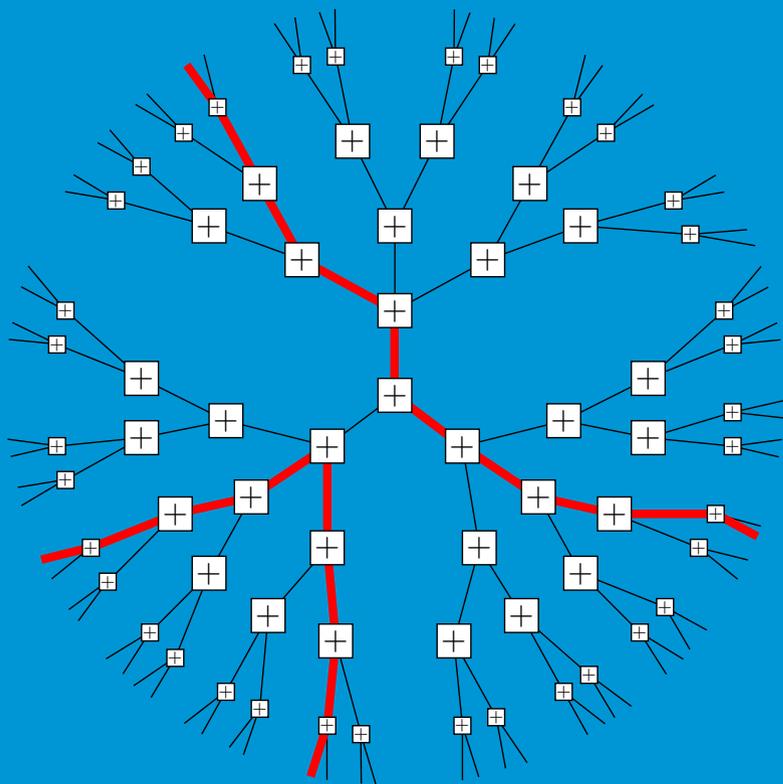
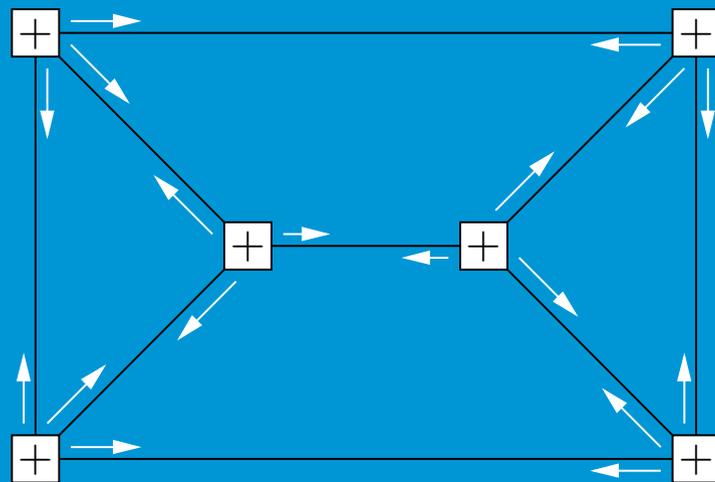
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Connection given by normal factor graph duality, cf. [Forney, 2001].



$$\zeta(V_1, \dots, V_n) = \sum_{\mathbf{k}} \zeta_{\mathbf{k}} \mathbf{V}^{\mathbf{k}} = \prod_{[\Gamma]} \frac{1}{1 - g(\Gamma, \mathbf{V})}$$

What Can a Power Series Do For You?

Consider the power series $\theta(V)$:

$$\theta(V) \triangleq \sum_k \theta_k V^k = 1V^0 + 2V^1 + 8V^3 + 16V^4 + 64V^6 + 128V^7 + \dots$$

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Consider the power series $\theta(V_1, \dots, V_n)$:

$$\theta(V_1, \dots, V_n) \triangleq \sum_{k_1, \dots, k_n} \theta_{k_1, \dots, k_n} V_1^{k_1} \cdots V_n^{k_n}$$

We can obtain **useful information** from

- ... the **exponent vectors** of $\theta(V_1, \dots, V_n)$
- ... the **coefficients** of $\theta(V_1, \dots, V_n)$
- ... the **evaluation** of $\theta(V_1, \dots, V_n)$ for some (V_1, \dots, V_n)
- ... the **convergence region** of $\theta(V_1, \dots, V_n)$
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Use of zeta functions for analyzing graphical models.

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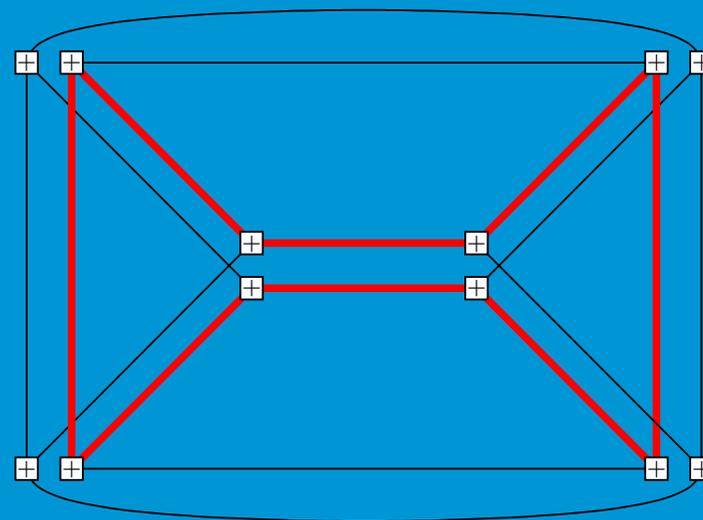
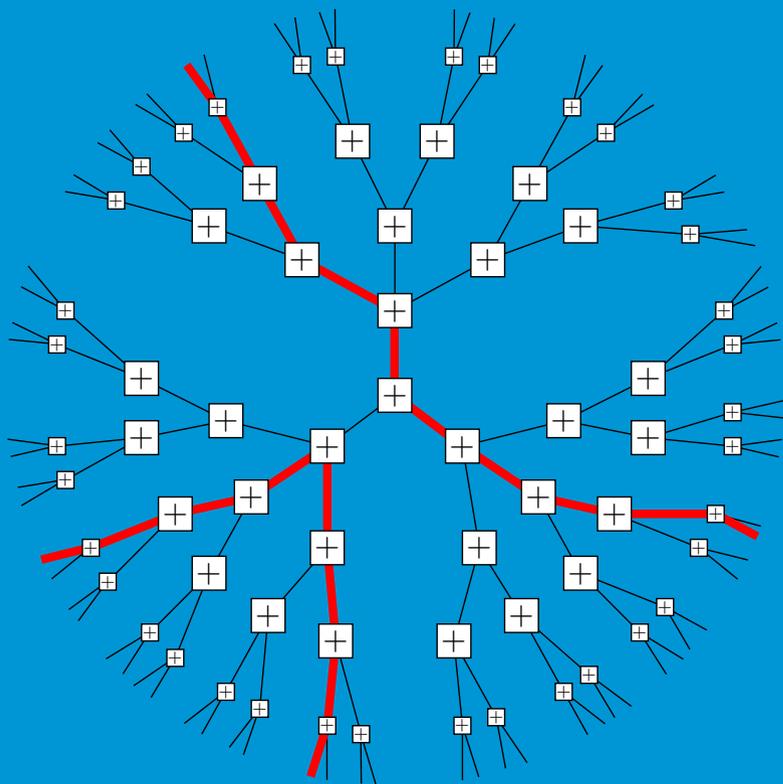
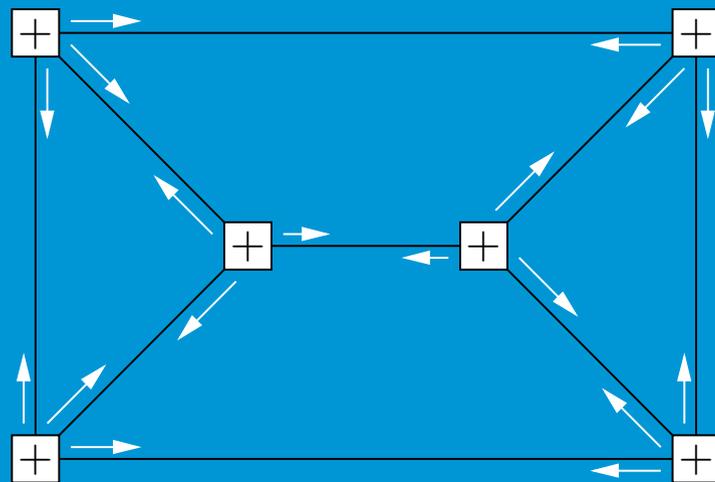
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Use of zeta functions for analyzing graphical models.



$$\zeta(V_1, \dots, V_n) = \sum_{\mathbf{k}} \zeta_{\mathbf{k}} \mathbf{V}^{\mathbf{k}} = \prod_{[\Gamma]} \frac{1}{1 - g(\Gamma, \mathbf{V})}$$

Communication Model



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Information word:

$$\mathbf{u} = (u_1, \dots, u_k) \in \mathcal{U}^k$$

Sent codeword:

$$\mathbf{x} = (x_1, \dots, x_n) \in \mathcal{C} \subseteq \mathcal{X}^n$$

Received word:

$$\mathbf{y} = (y_1, \dots, y_n) \in \mathcal{Y}^n$$

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Decoding: Based on \mathbf{y} we would like to estimate the transmitted codeword $\hat{\mathbf{x}}$ or the information word $\hat{\mathbf{u}}$.

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Depending on what criterion we optimize, we obtain different **decoding algorithms**.

Symbol-Wise MAP Decoding (Part 1)



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Minimizing the symbol error probability (for each $i = 1, \dots, k$) results in **symbol-wise MAP decoding**.

For each $i = 1, \dots, k$:

$$\hat{u}_i^{\text{symbol}}(\mathbf{y}) = \operatorname{argmax}_{u_i \in \mathcal{U}} P_{U_i|\mathbf{Y}}(u_i|\mathbf{y}) = \operatorname{argmax}_{u_i \in \mathcal{U}} P_{U_i, \mathbf{Y}}(u_i, \mathbf{y}).$$

Symbol-Wise MAP Decoding (Part 2)

Rewriting **symbol-wise MAP decoding** for symbol i we obtain

$$\hat{u}_i^{\text{symbol}}(\mathbf{y}) = \operatorname{argmax}_{u_i \in \mathcal{U}} P_{U_i, \mathbf{Y}}(u_i, \mathbf{y})$$

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$$\begin{aligned}\hat{u}_i^{\text{symbol}}(\mathbf{y}) &= \operatorname{argmax}_{u_i \in \mathcal{U}} P_{U_i, \mathbf{Y}}(u_i, \mathbf{y}) \\ &= \underbrace{\operatorname{argmax}_{u_i \in \mathcal{U}}}_{\substack{\mathbf{u} \in \mathcal{U}^k, \mathbf{x} \in \mathcal{X}^n \\ u_i \text{ fixed}}} \sum_{\substack{\mathbf{u} \in \mathcal{U}^k, \mathbf{x} \in \mathcal{X}^n \\ u_i \text{ fixed}}} \underbrace{P_{\mathbf{U}\mathbf{X}\mathbf{Y}}(\mathbf{u}, \mathbf{x}, \mathbf{y})}_{\substack{\mathbf{u} \in \mathcal{U}^k, \mathbf{x} \in \mathcal{X}^n \\ u_i \text{ fixed}}}\end{aligned}$$

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$$\begin{aligned} \hat{u}_i^{\text{symbol}}(\mathbf{y}) &= \operatorname{argmax}_{u_i \in \mathcal{U}} P_{U_i, \mathbf{Y}}(u_i, \mathbf{y}) \\ &= \underbrace{\operatorname{argmax}_{u_i \in \mathcal{U}}}_{\substack{\mathbf{u} \in \mathcal{U}^k, \mathbf{x} \in \mathcal{X}^n \\ u_i \text{ fixed}}} \underbrace{\sum_{\substack{\mathbf{u} \in \mathcal{U}^k, \mathbf{x} \in \mathcal{X}^n \\ u_i \text{ fixed}}} \underbrace{P_{\mathbf{U}\mathbf{X}\mathbf{Y}}(\mathbf{u}, \mathbf{x}, \mathbf{y})}_{\text{Joint pmf/pdf}}}_{\text{Joint pmf/pdf}} \end{aligned}$$

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Binary Linear Codes

Let **H** be a parity-check matrix, e.g.

$$\mathbf{H} = \begin{pmatrix} 1 & 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 1 \end{pmatrix}.$$

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The code \mathcal{C} described by \mathbf{H} is then

$$\mathcal{C} = \left\{ (x_1, x_2, x_3, x_4, x_5) \in \mathbb{F}_2^5 \mid \mathbf{H} \cdot \mathbf{x}^T = \mathbf{0}^T \pmod{2} \right\}.$$

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A vector $\mathbf{x} \in \mathbb{F}_2^5$ is a codeword if and only if

$$\mathbf{H} \cdot \mathbf{x}^T = \mathbf{0}^T \pmod{2}.$$

Binary Linear Codes

This means that \mathbf{x} is a codeword if and only if \mathbf{x} fulfills the following two equations:

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In summary,

$$\begin{aligned} \mathcal{C} &= \left\{ (x_1, x_2, x_3, x_4, x_5) \in \mathbb{F}_2^5 \mid \mathbf{H} \cdot \mathbf{x}^T = \mathbf{0}^T \pmod{2} \right\} \\ &= \left\{ (x_1, x_2, x_3, x_4, x_5) \in \mathbb{F}_2^5 \mid \begin{aligned} x_1 + x_2 + x_3 &= 0 \pmod{2} \\ x_2 + x_4 + x_5 &= 0 \pmod{2} \end{aligned} \right\}. \end{aligned}$$

Graphical Representation of a Code

$$\mathbf{H} = \begin{pmatrix} 1 & 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 1 \end{pmatrix}$$

x_1 ○

x_2 ○

x_3 ○

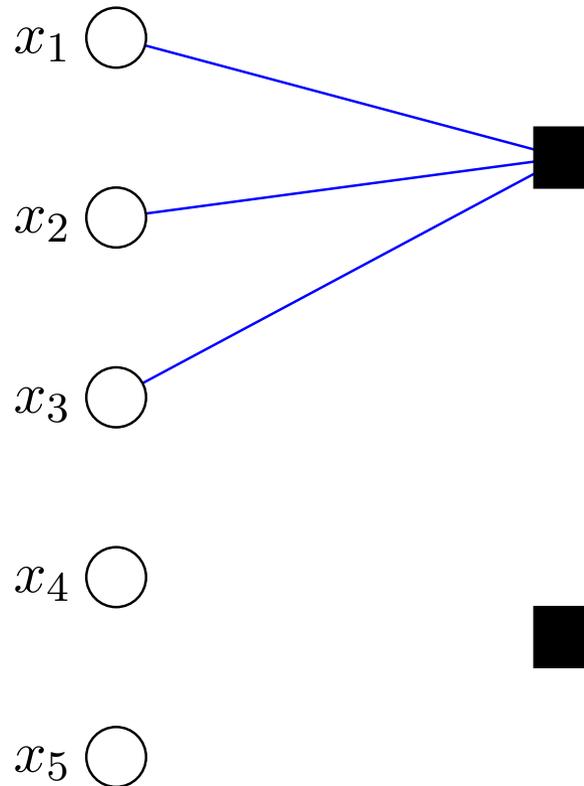
x_4 ○

x_5 ○



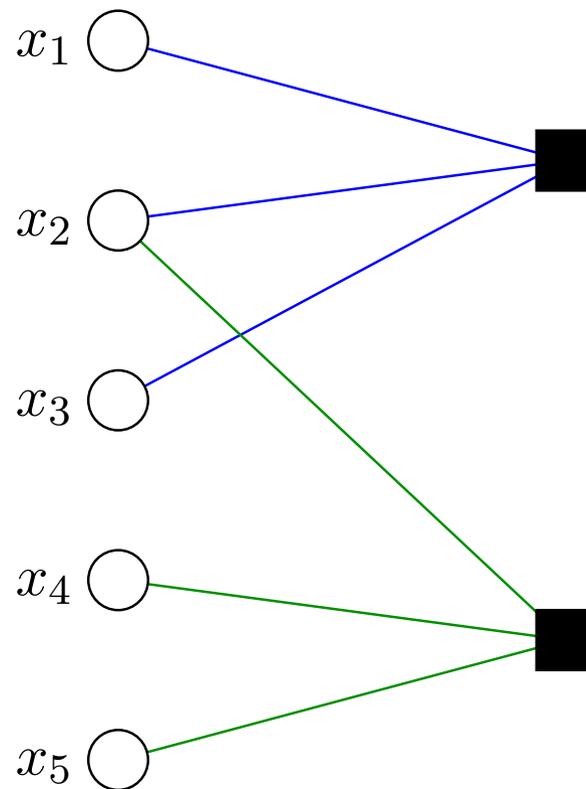
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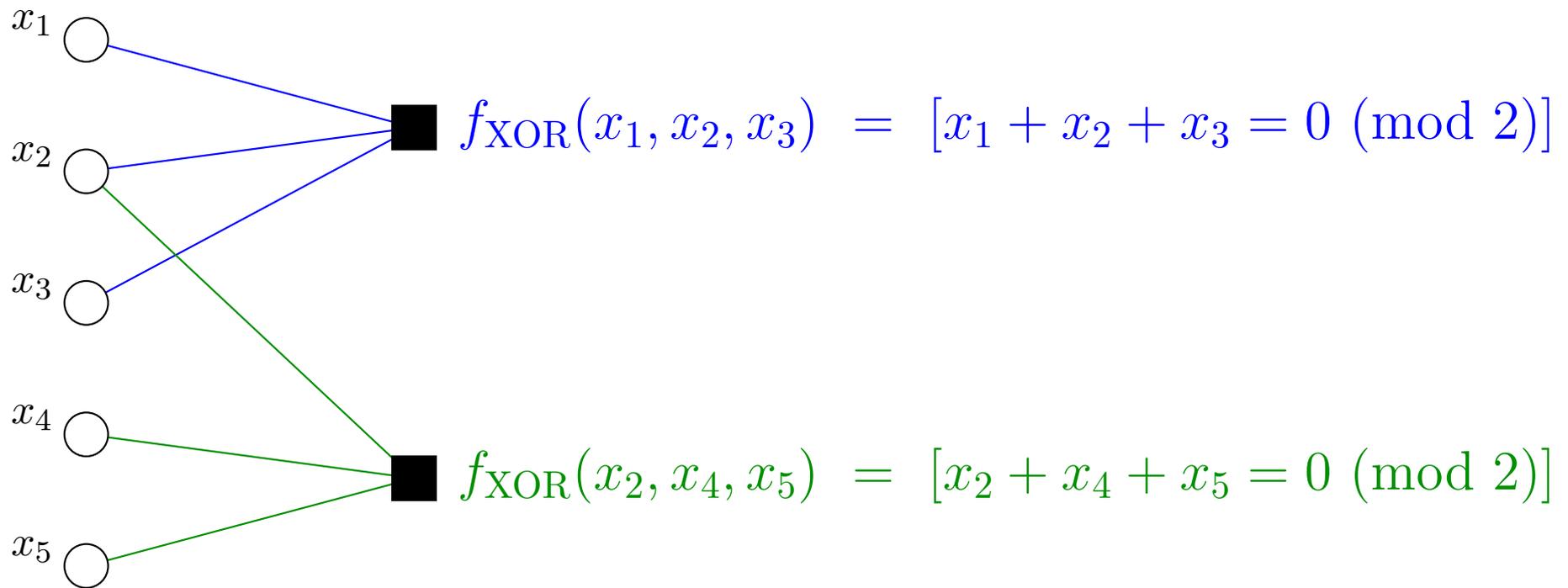
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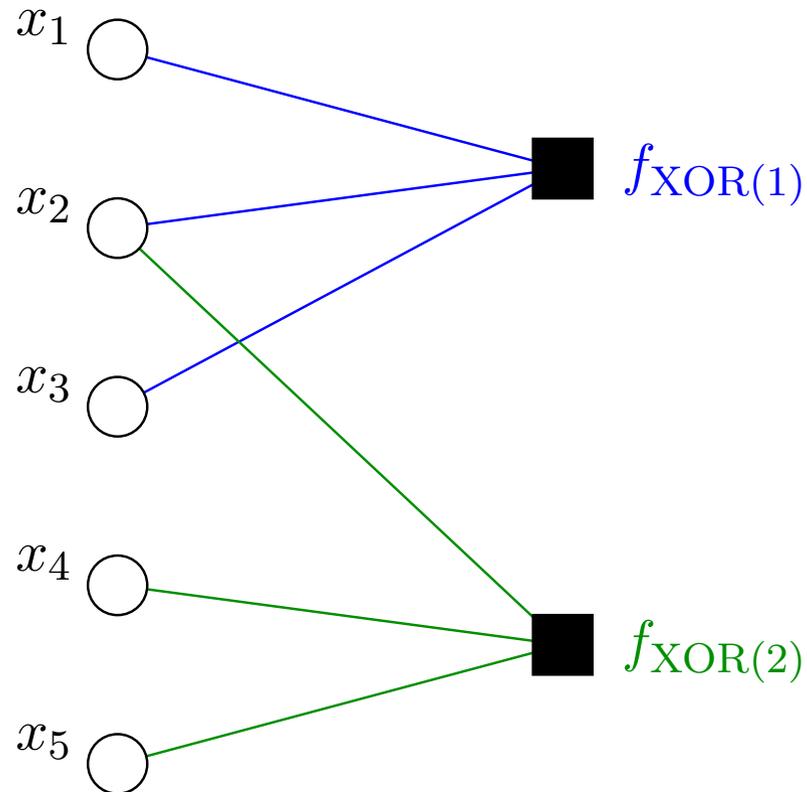
FG of a Data Communication System based on a parity-check code

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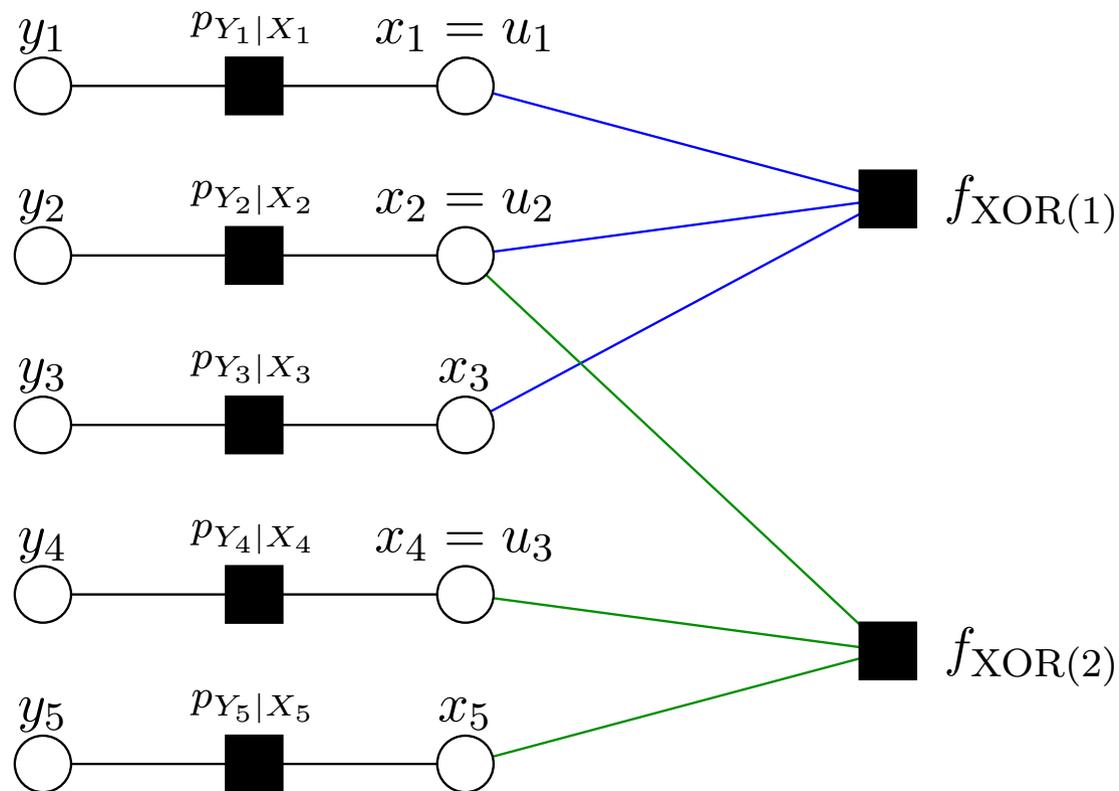
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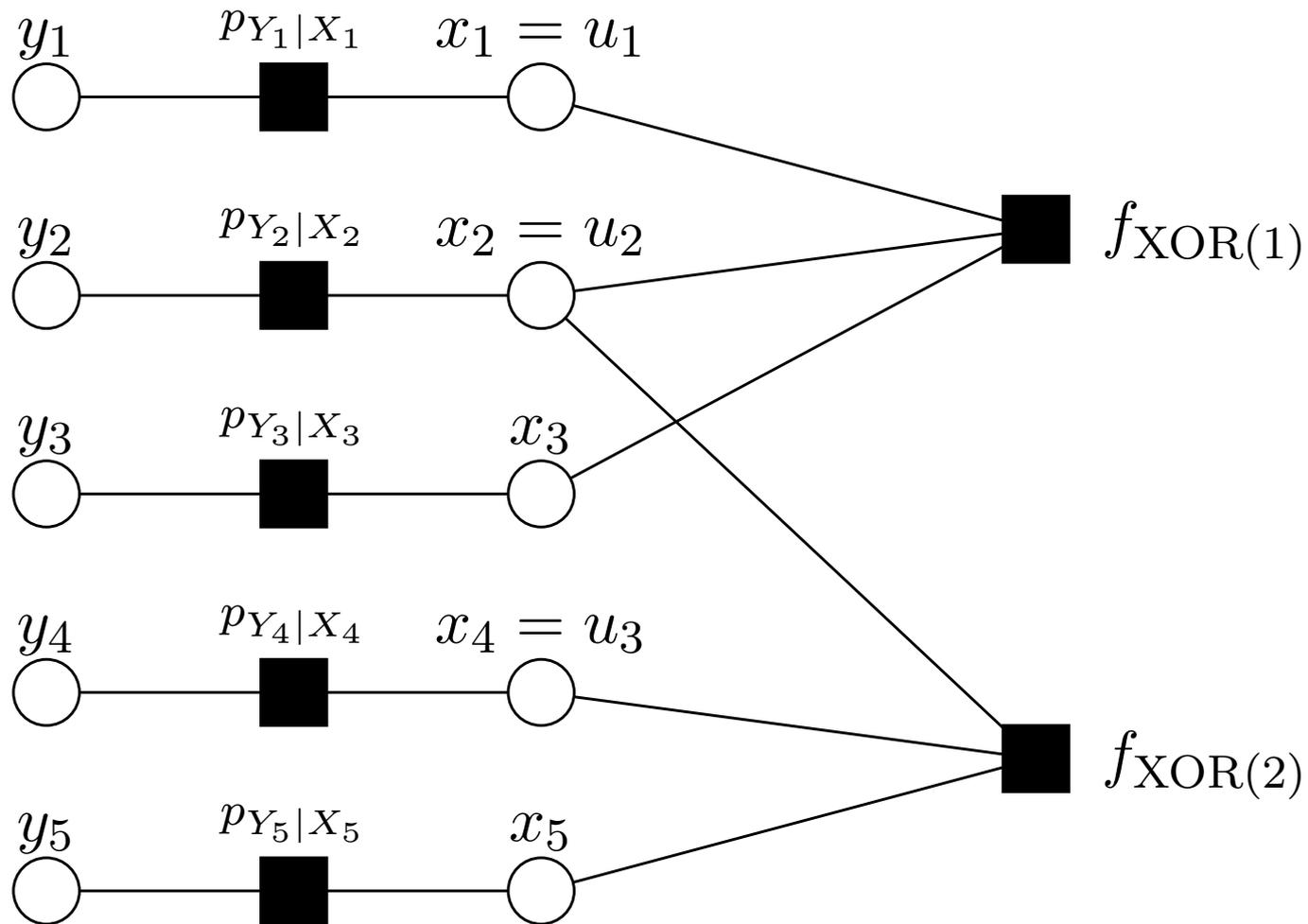
Symbol-Wise MAP Decoding

Remember, **symbol-wise MAP decoding** for symbol i can be written as

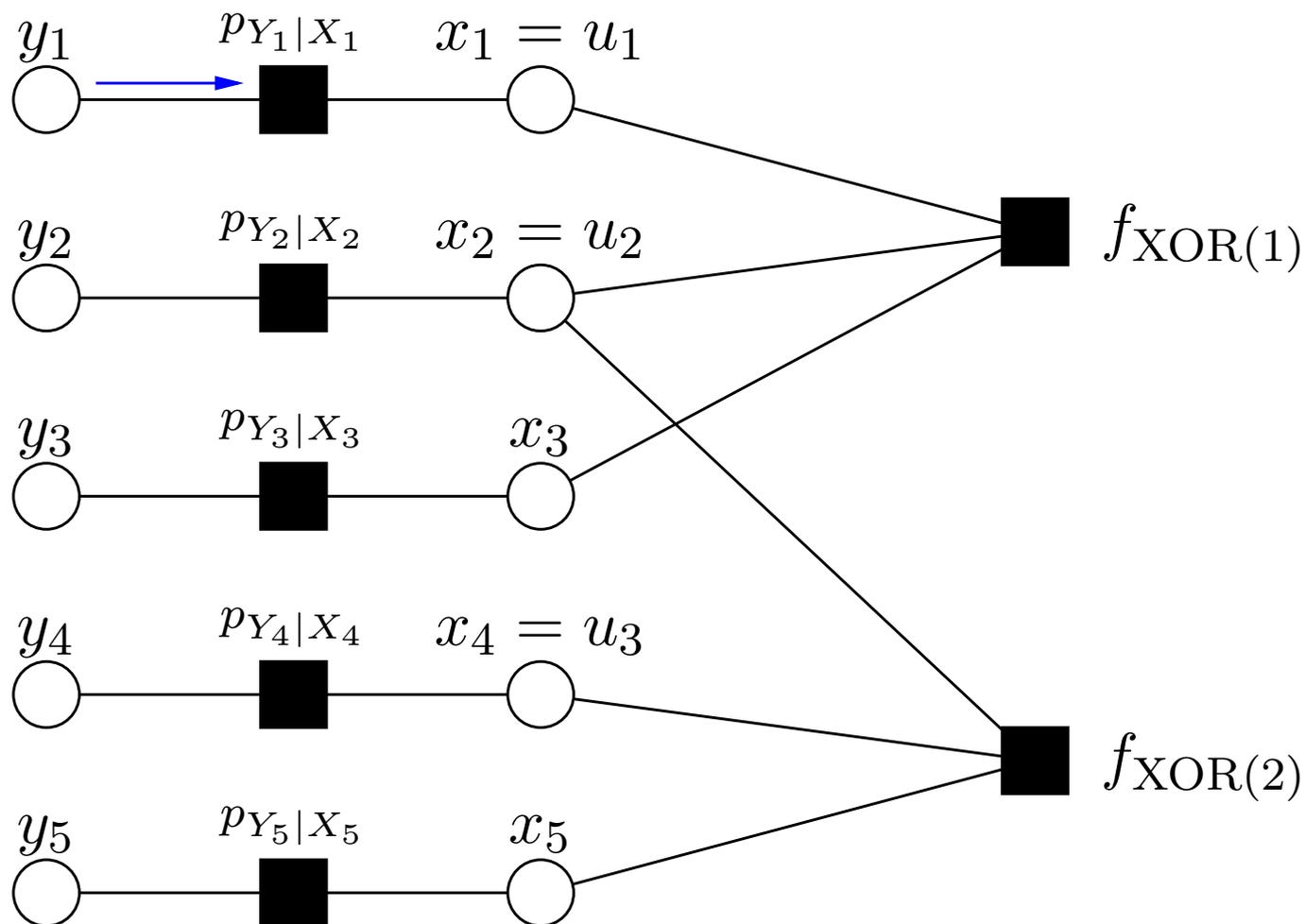
$$\hat{u}_i^{\text{symbol}}(\mathbf{y}) = \underbrace{\operatorname{argmax}_{u_i \in \mathcal{U}}}_{\text{Decision taking}} \underbrace{\sum_{\substack{\mathbf{u} \in \mathcal{U}^k, \mathbf{x} \in \mathcal{X}^n \\ u_i \text{ fixed}}} \underbrace{P_{\mathbf{U}\mathbf{X}\mathbf{Y}}(\mathbf{u}, \mathbf{x}, \mathbf{y})}_{\text{Joint pmf/pdf}}}_{\text{Marginal function}}$$

Decision about symbol u_i based on symbol-wise decoding

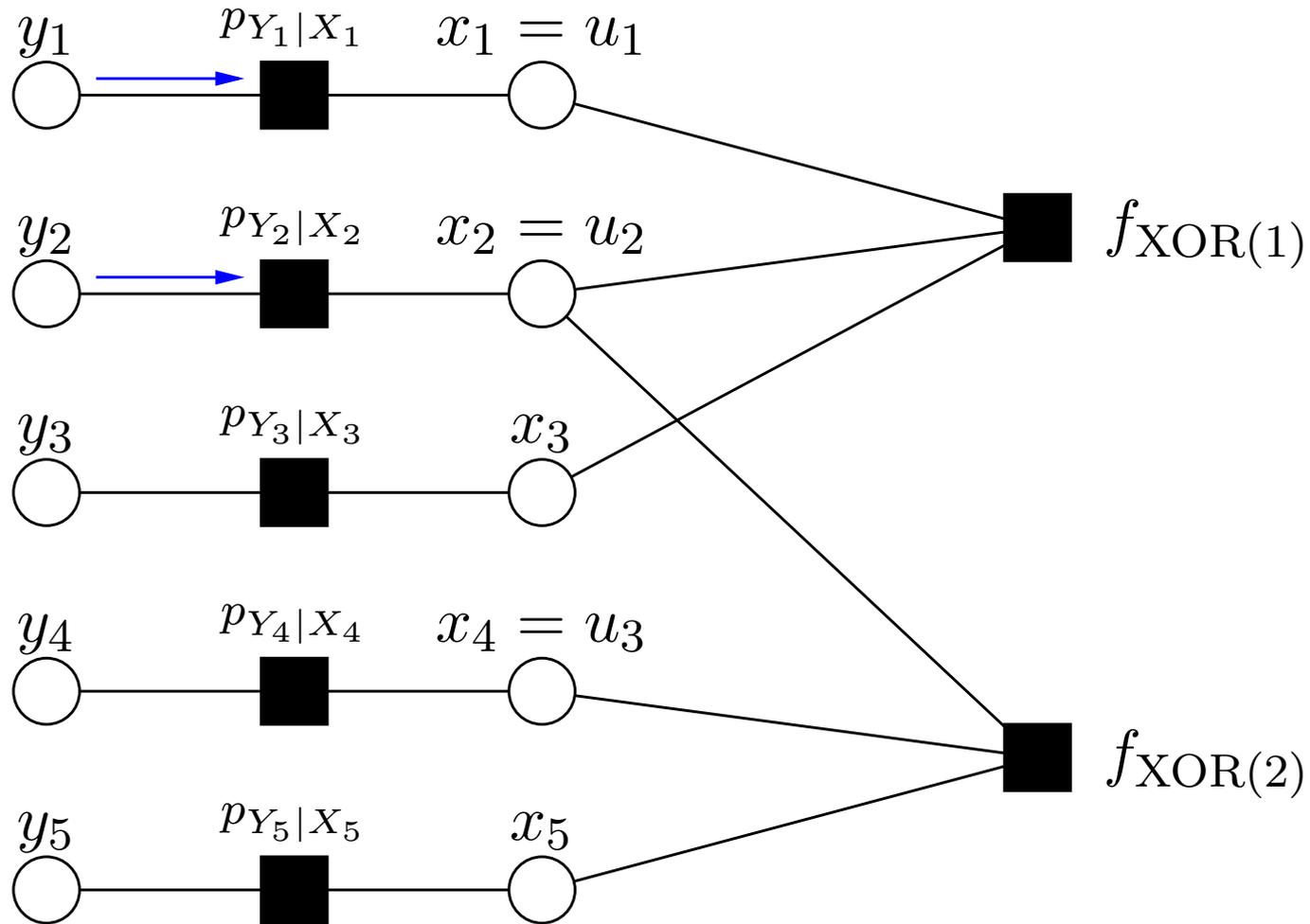
SPA Decoding (Factor graph without cycles)



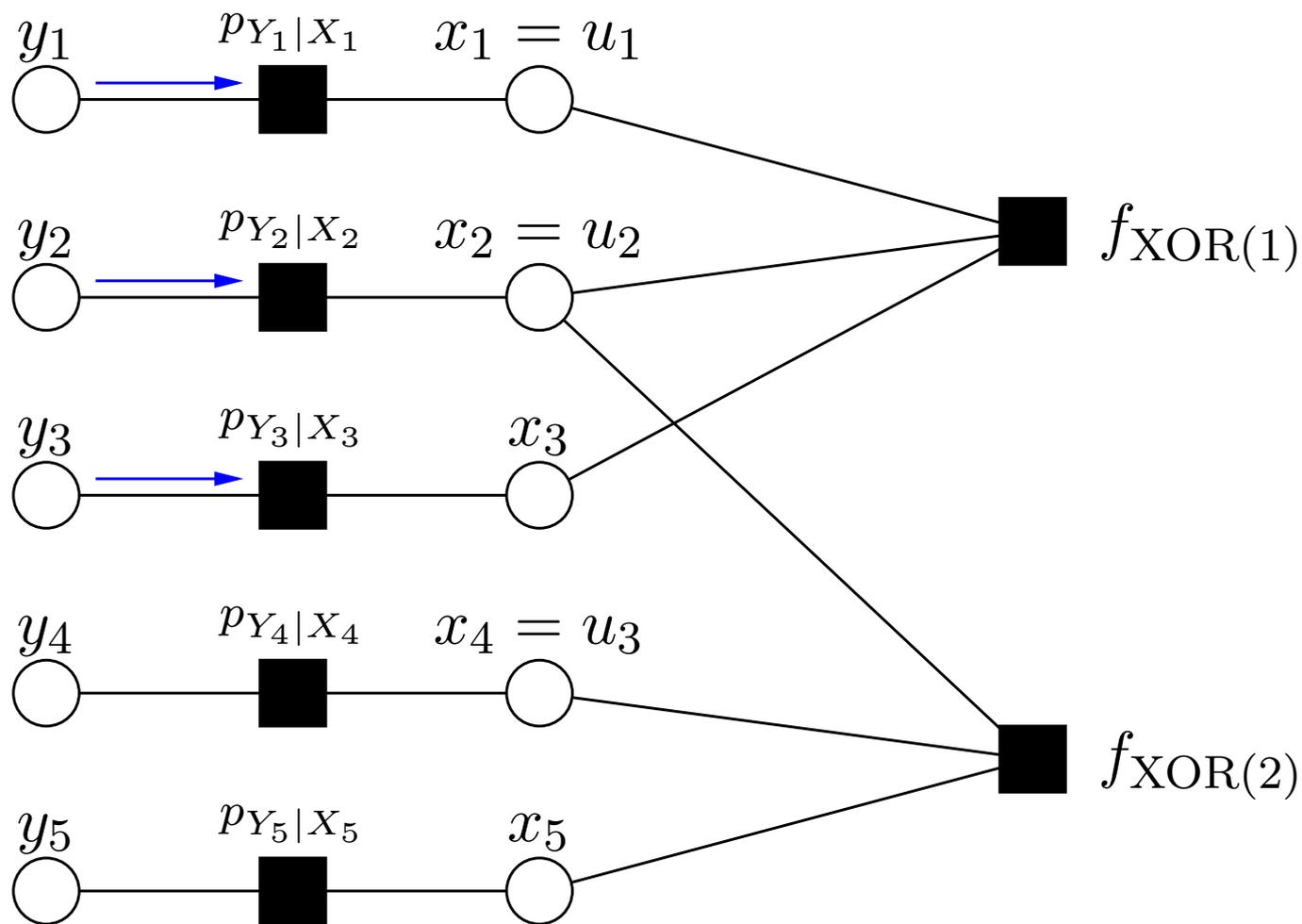
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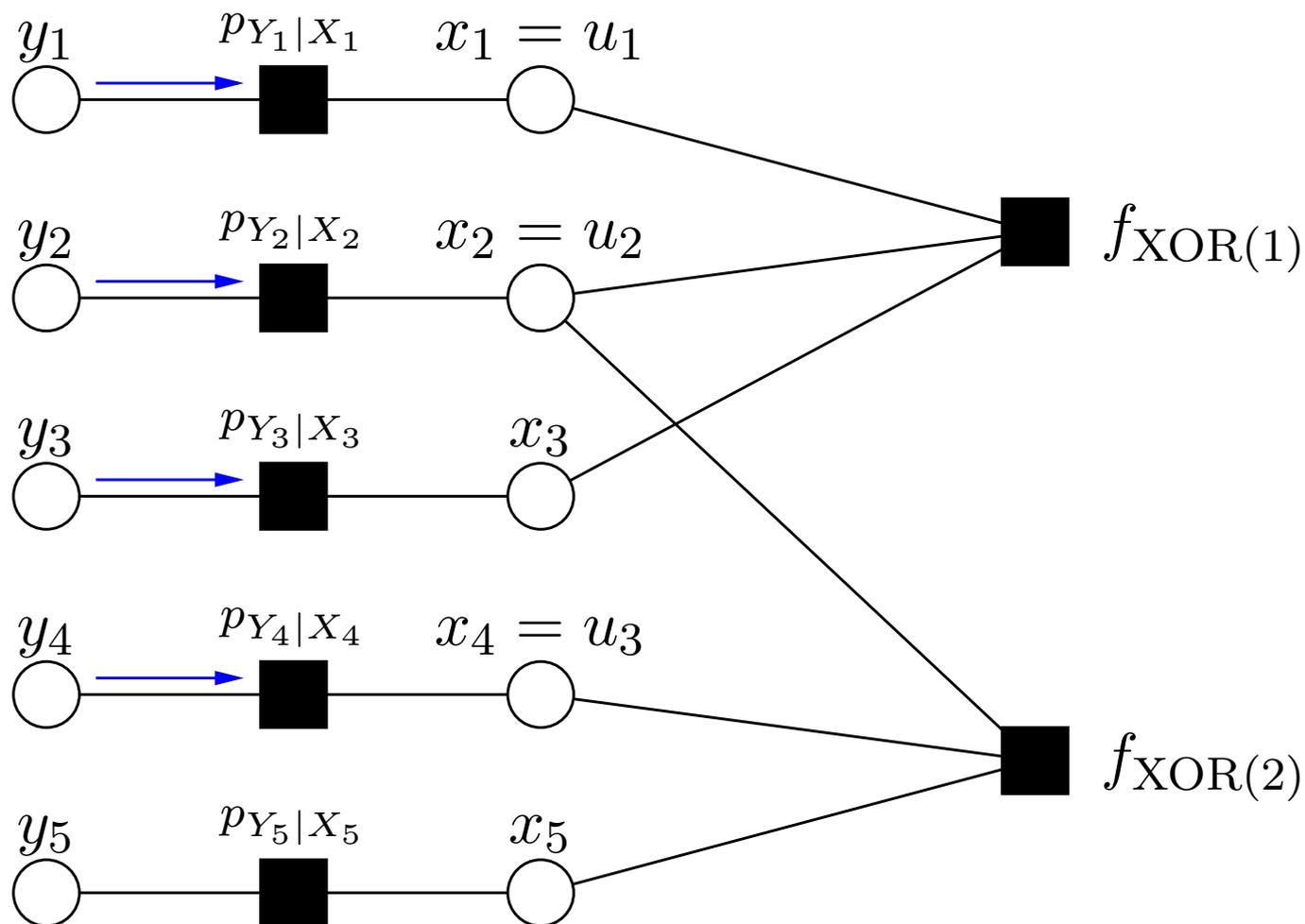
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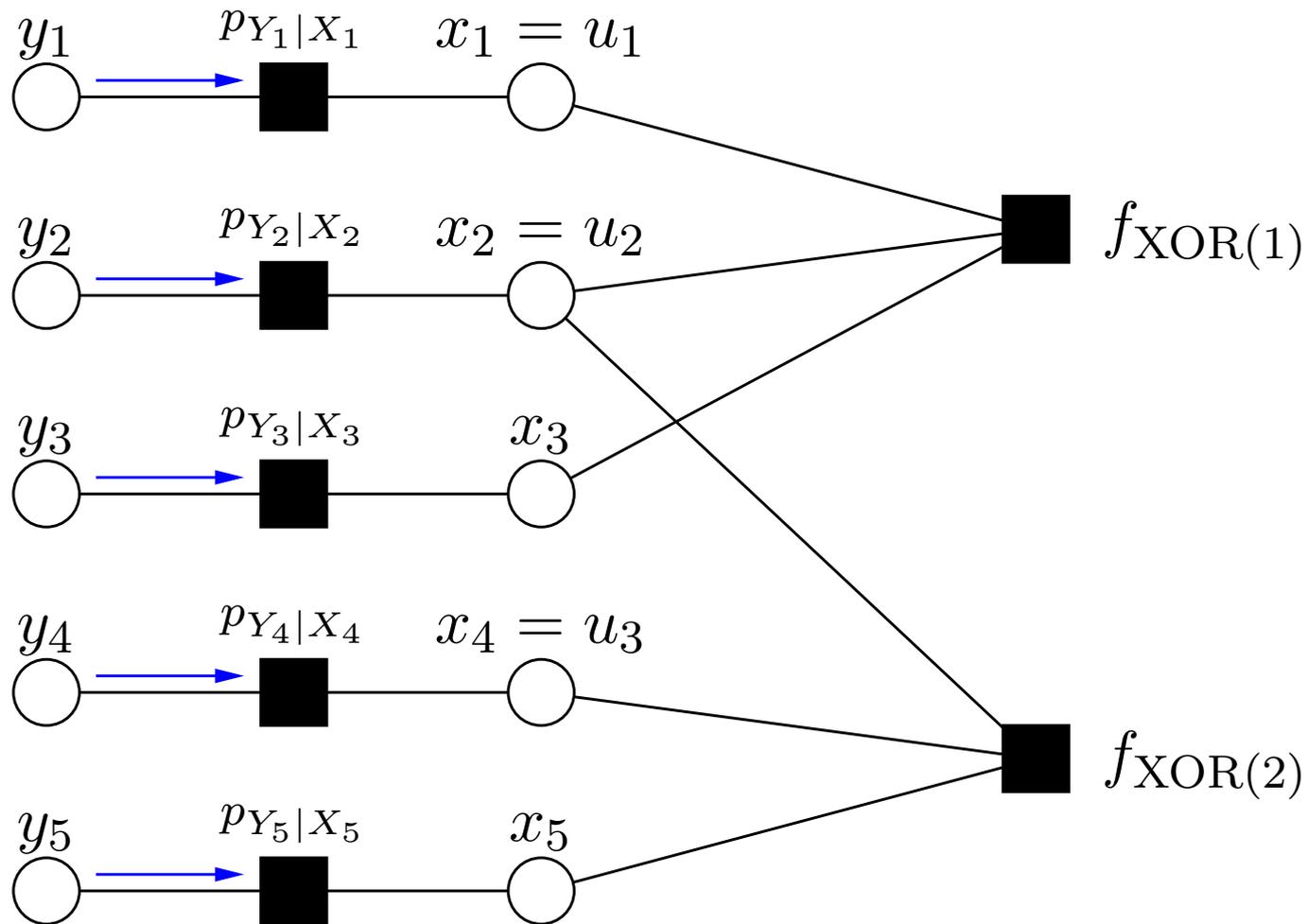
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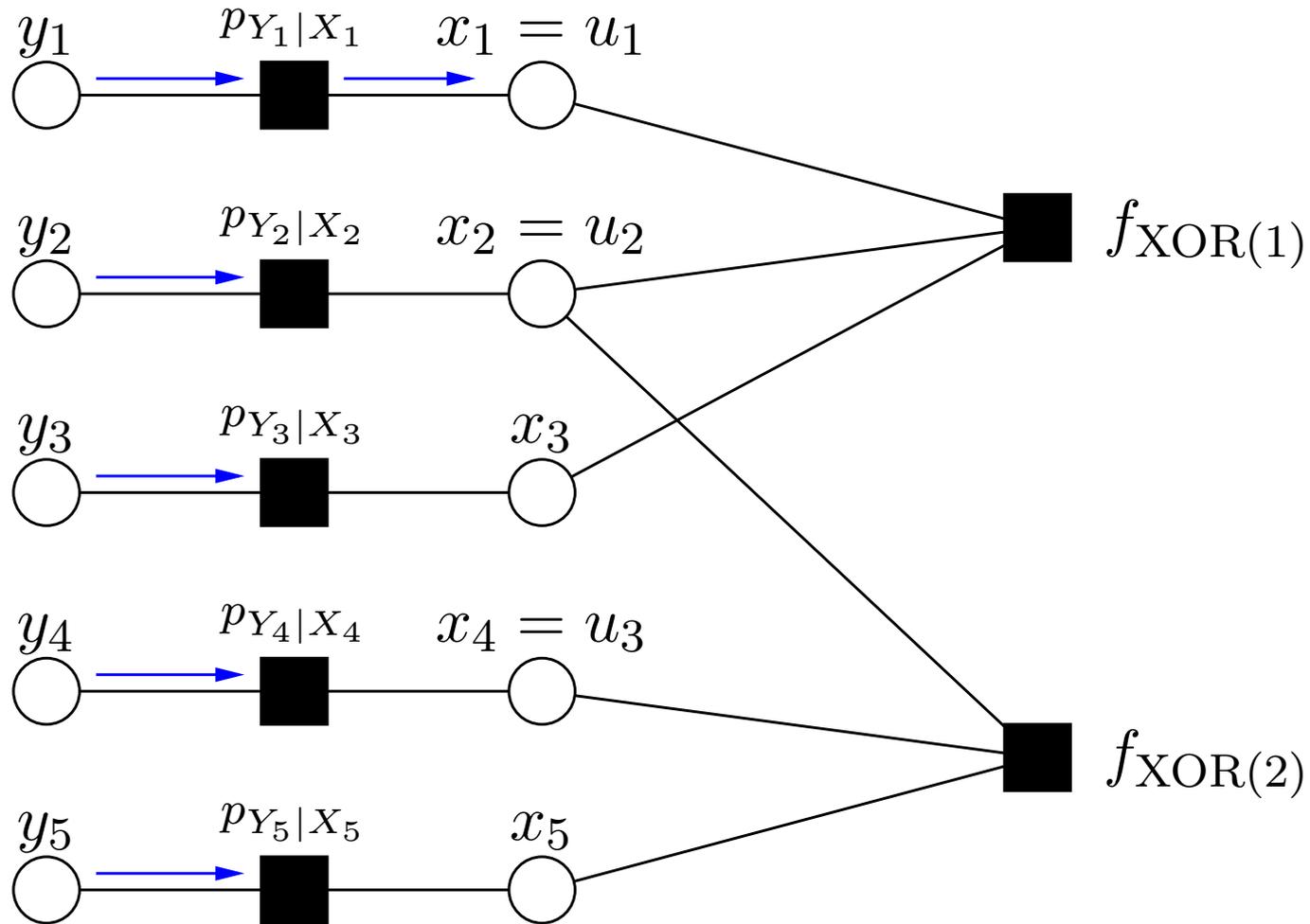
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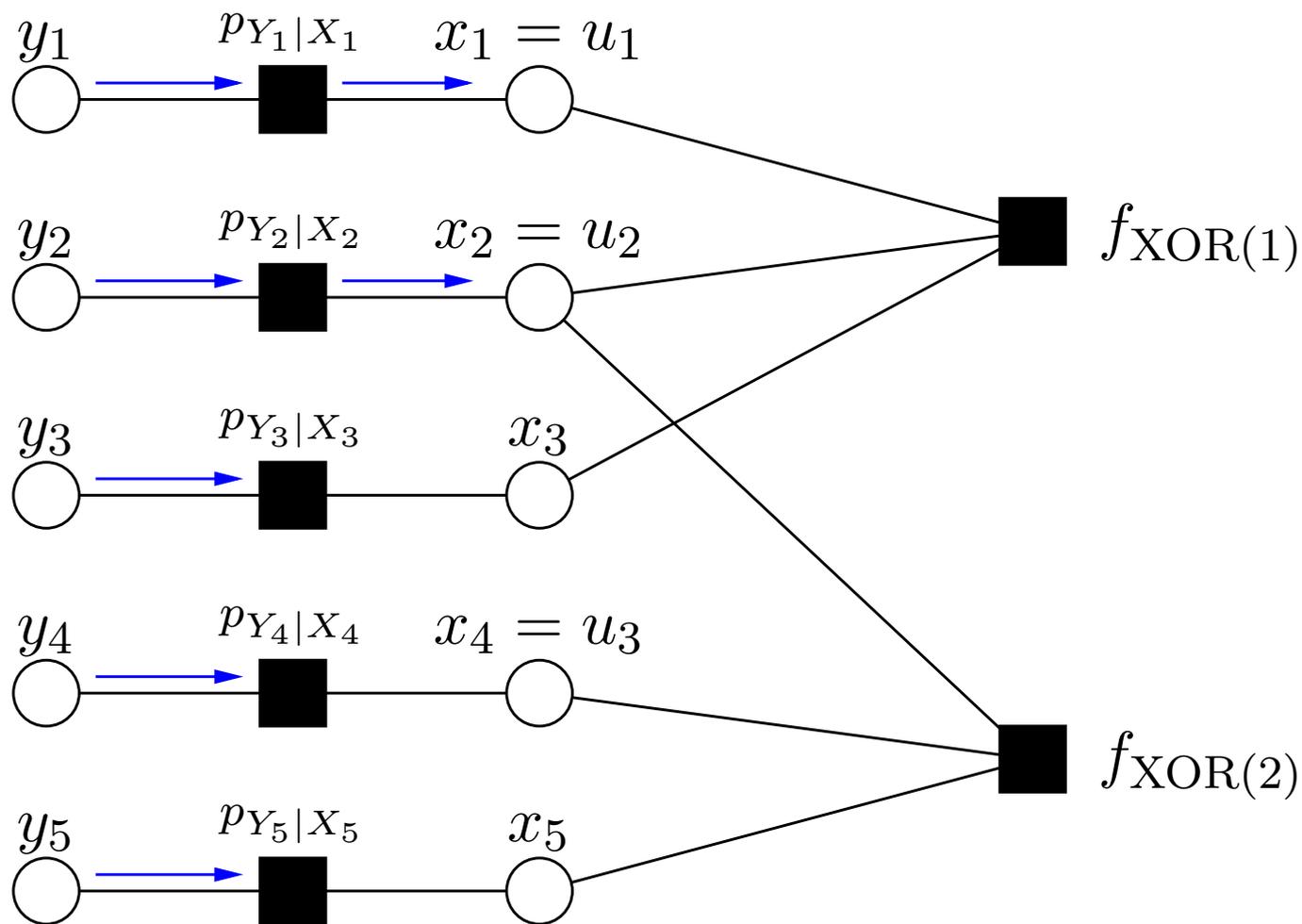
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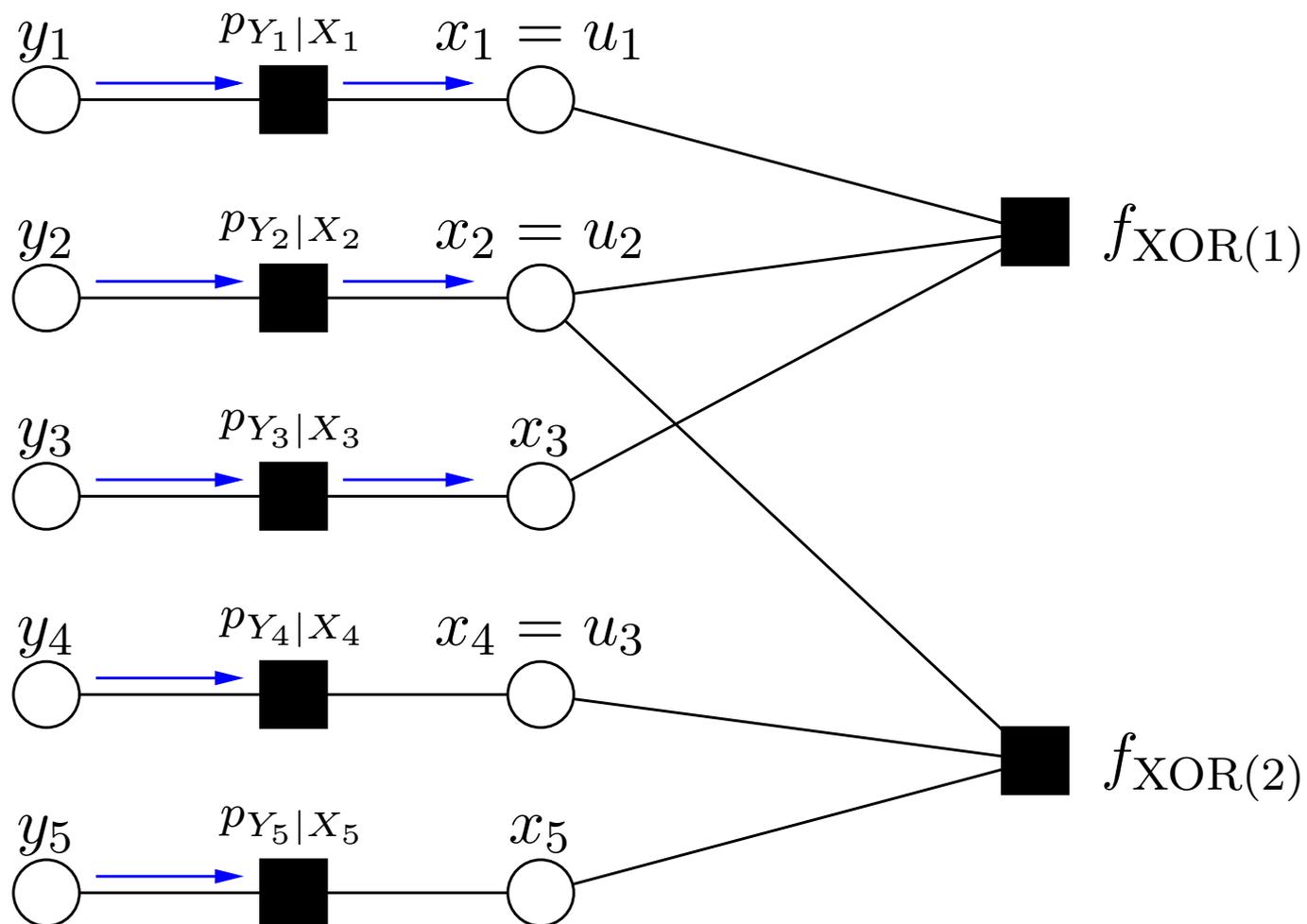
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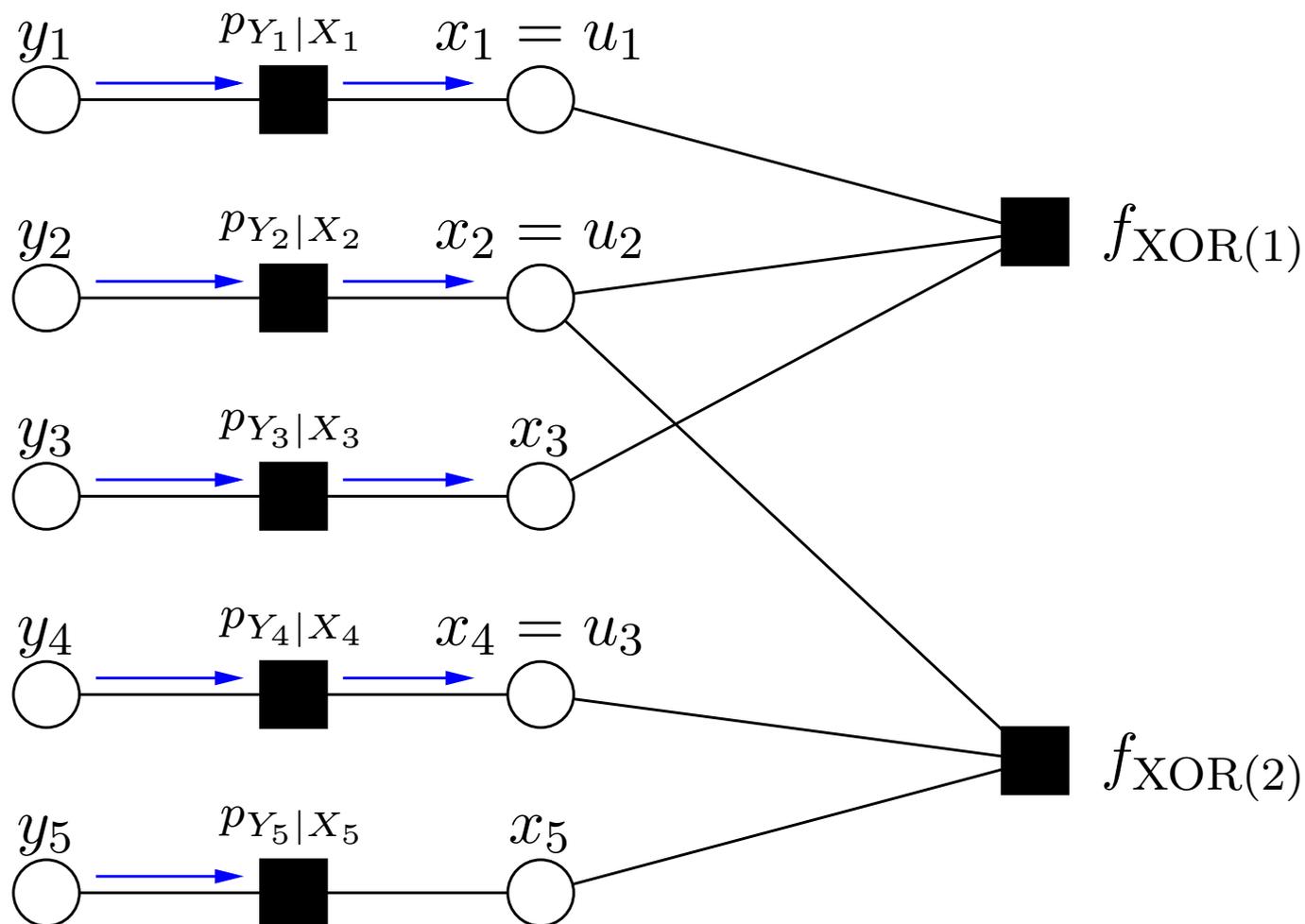
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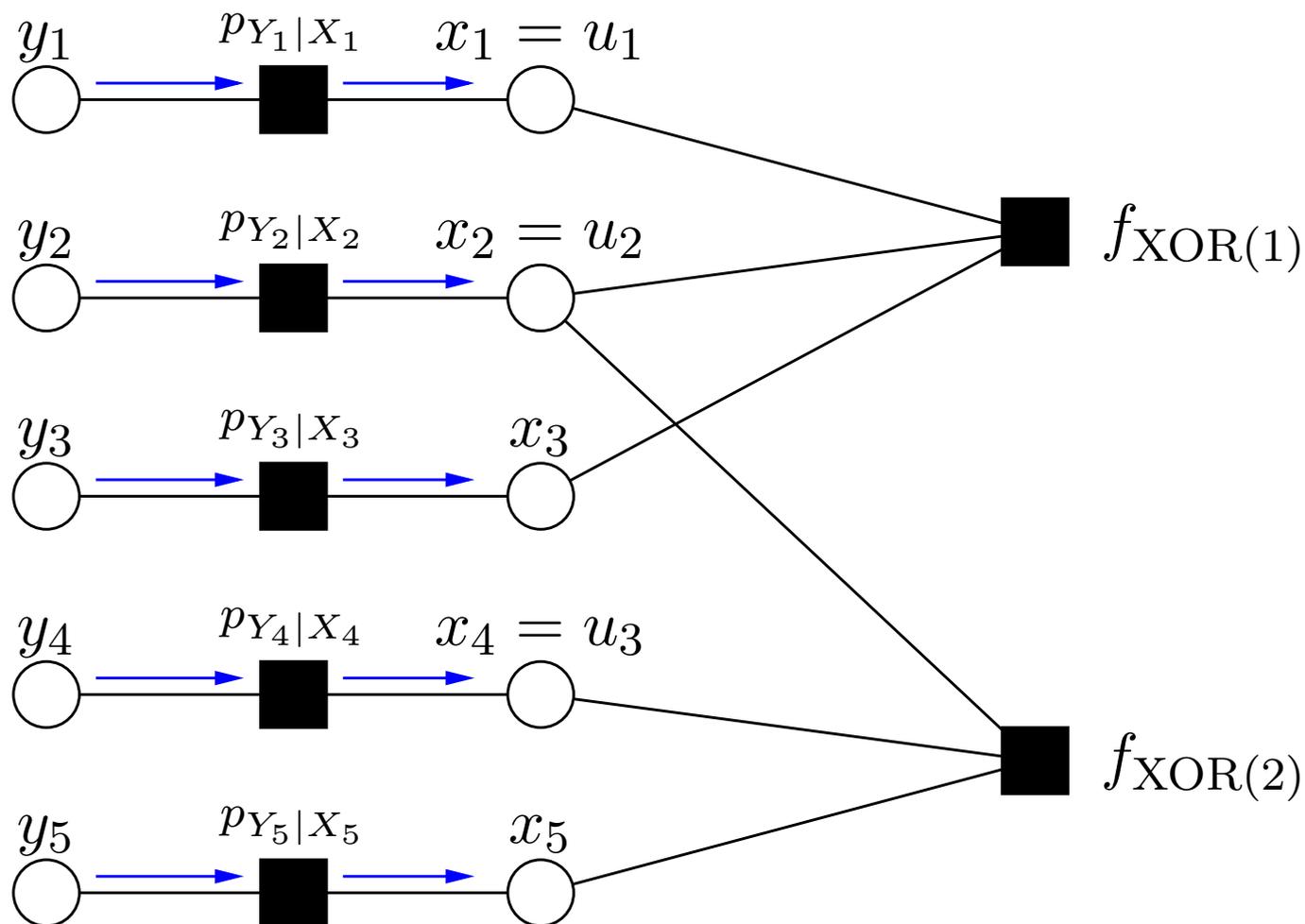
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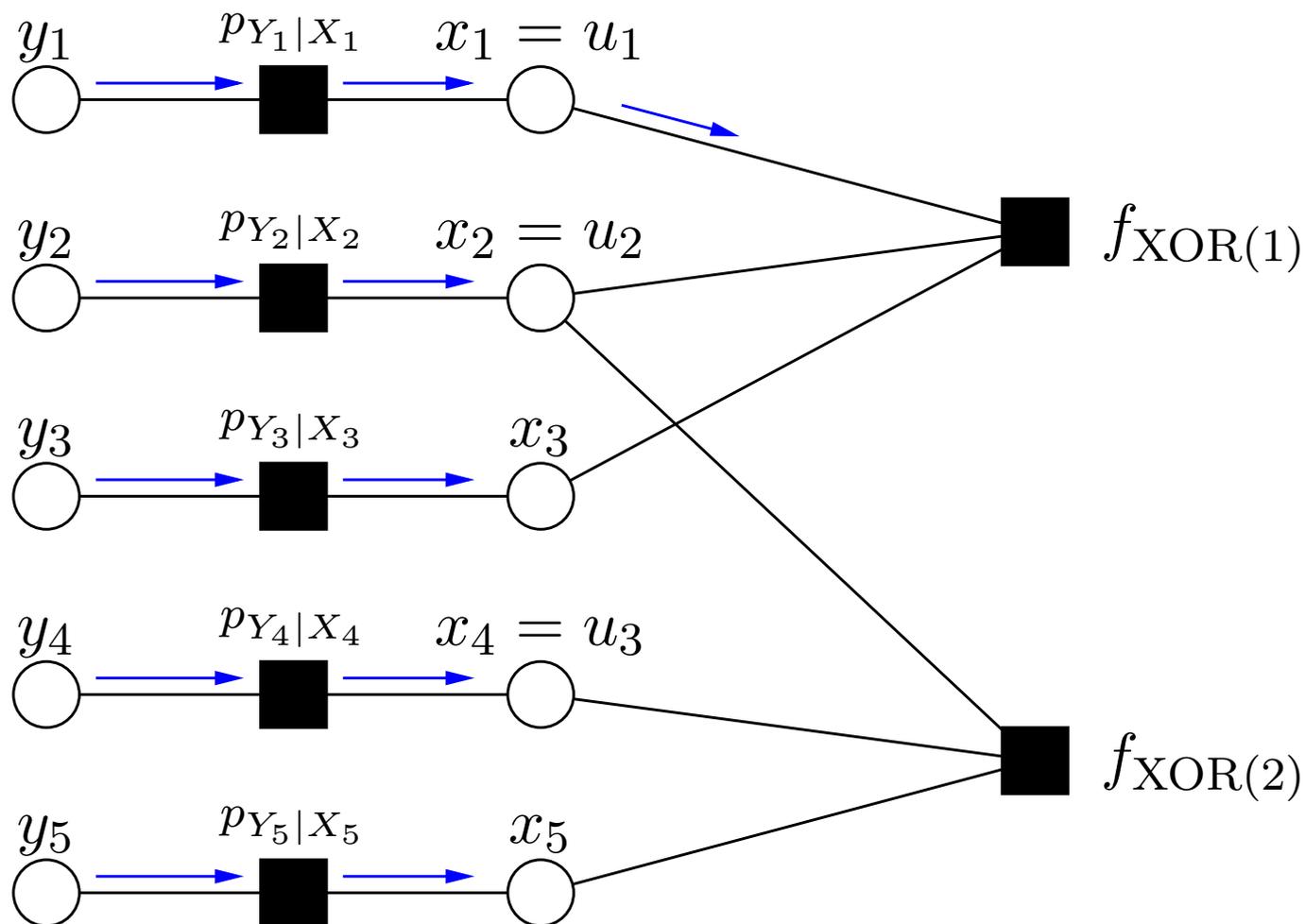
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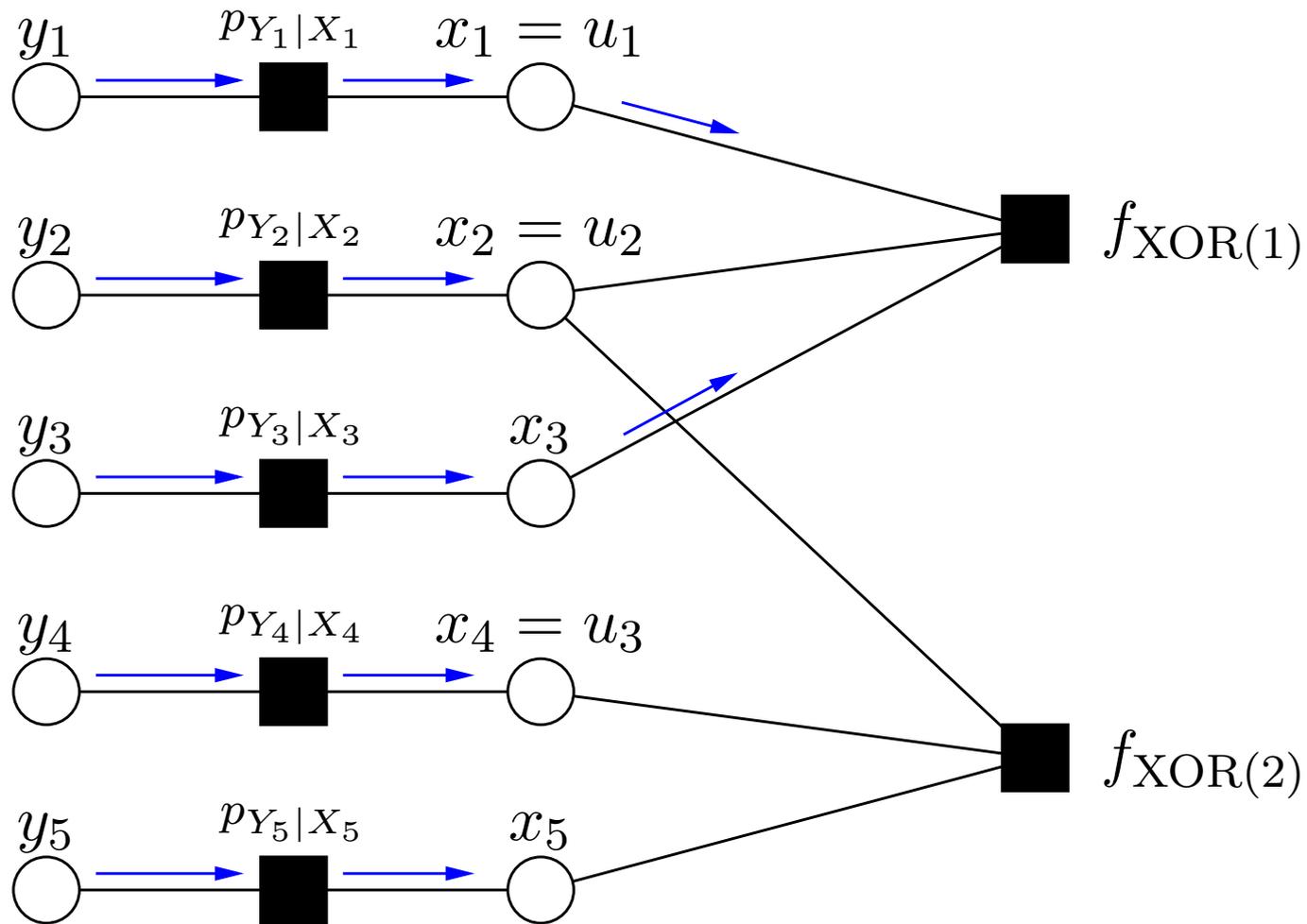
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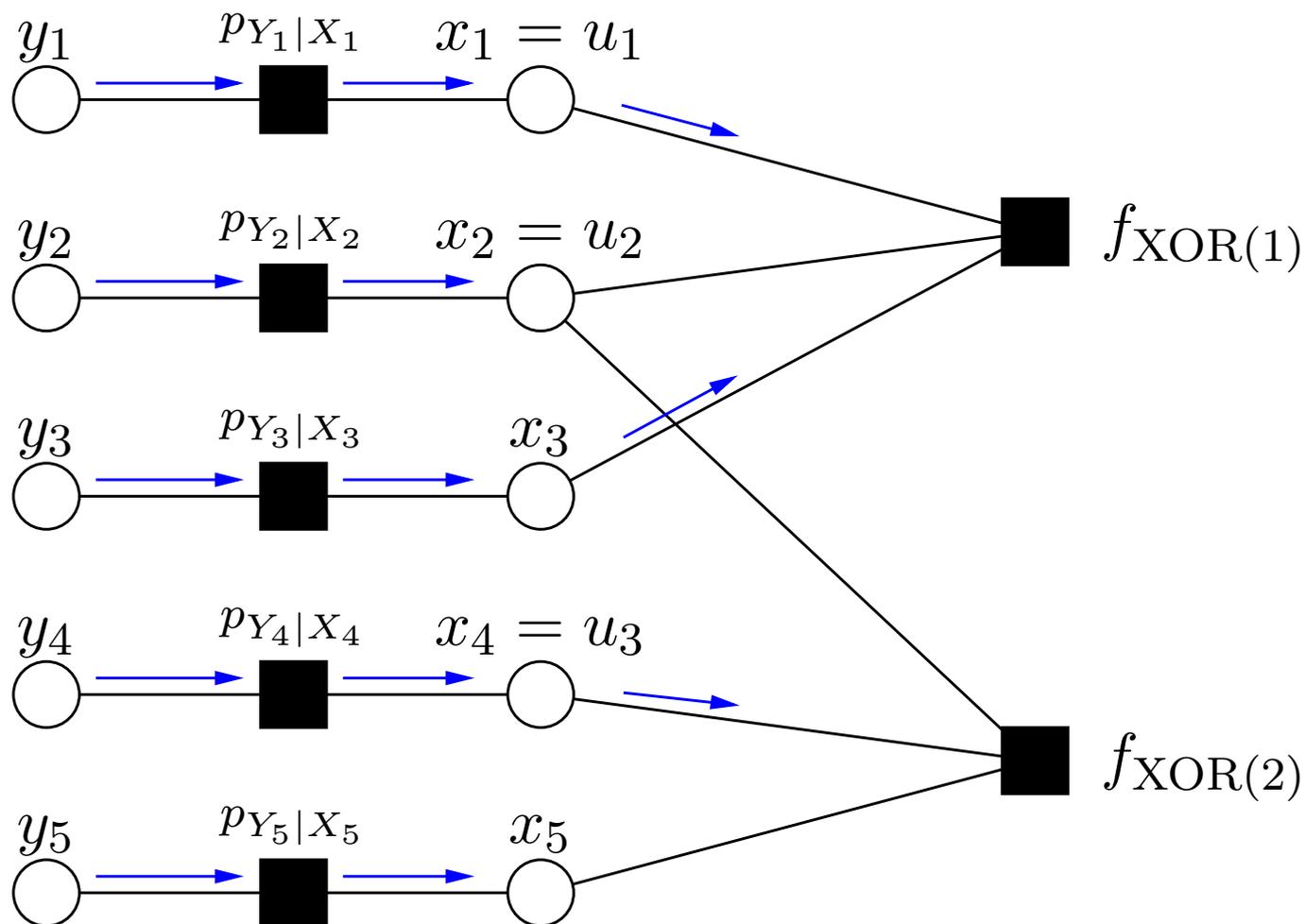
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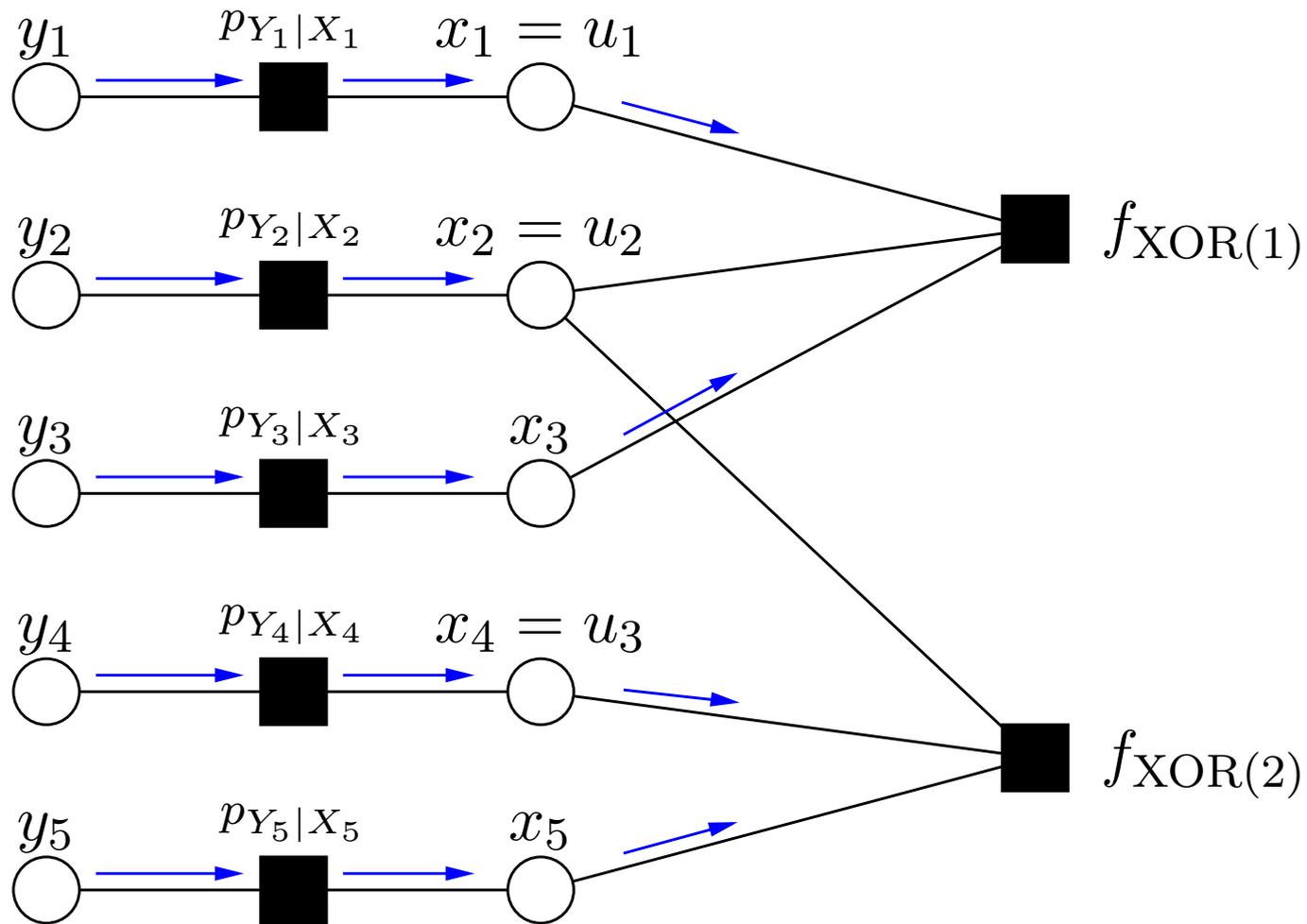
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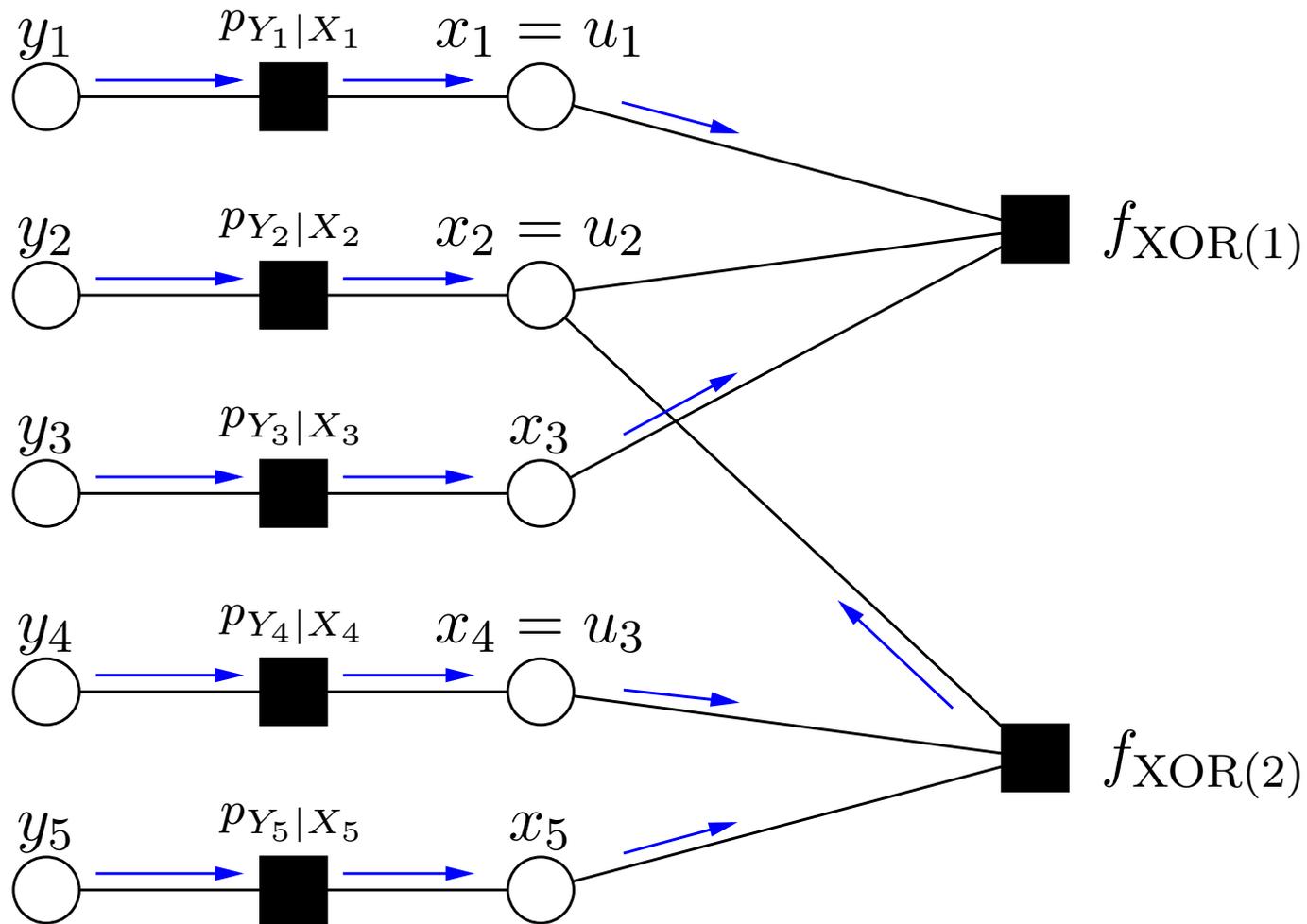
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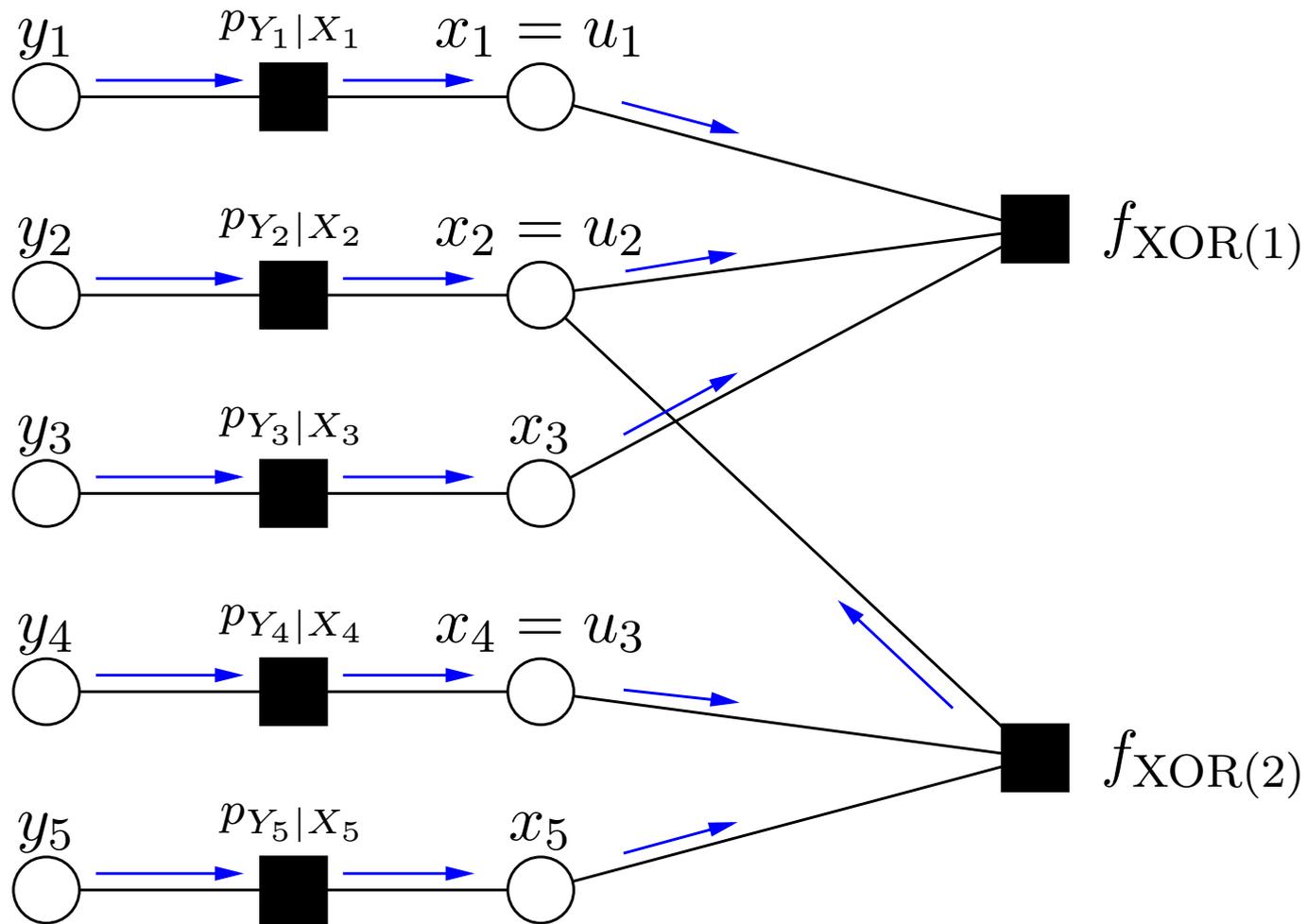
SPA Decoding (Factor graph without cycles)



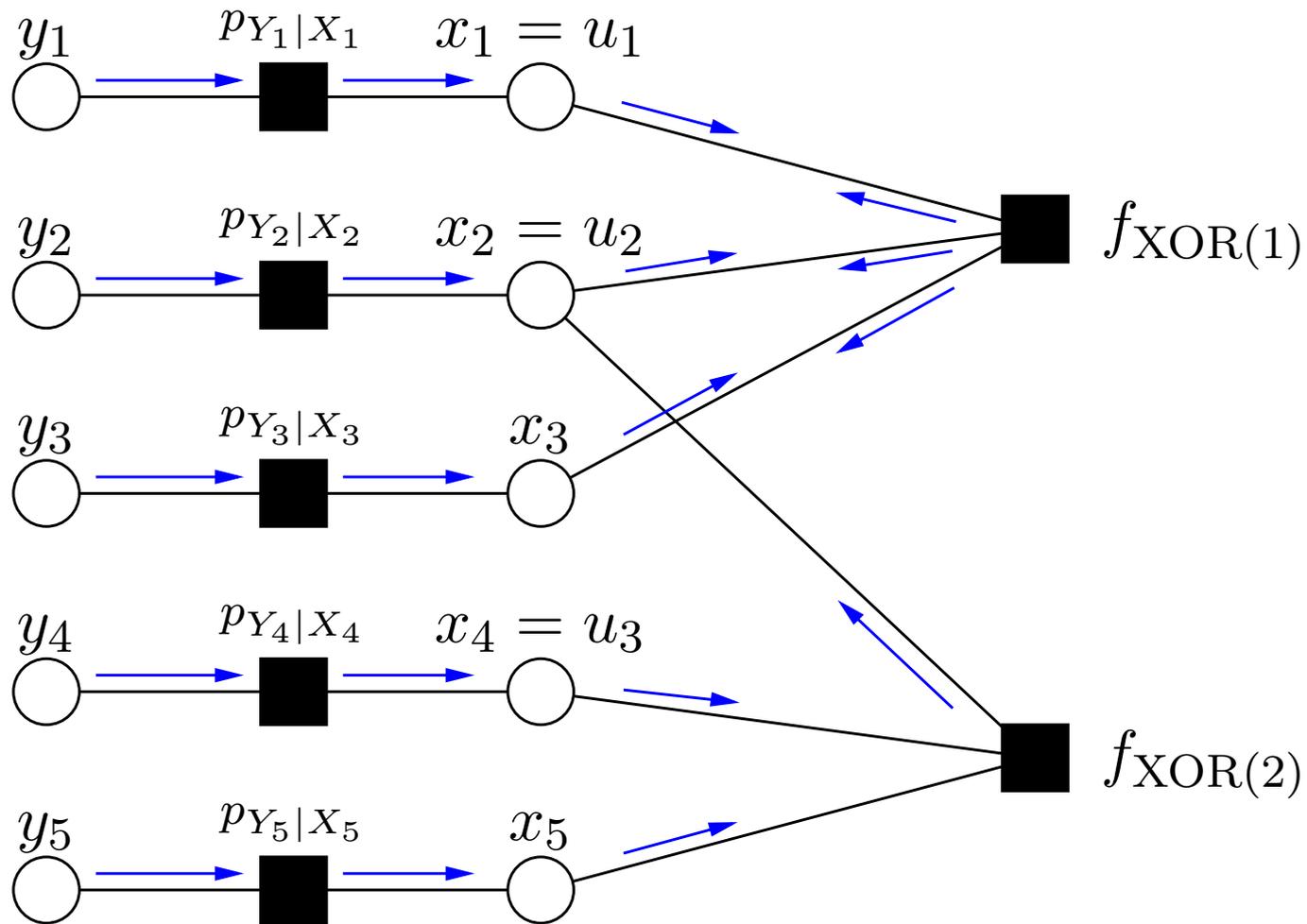
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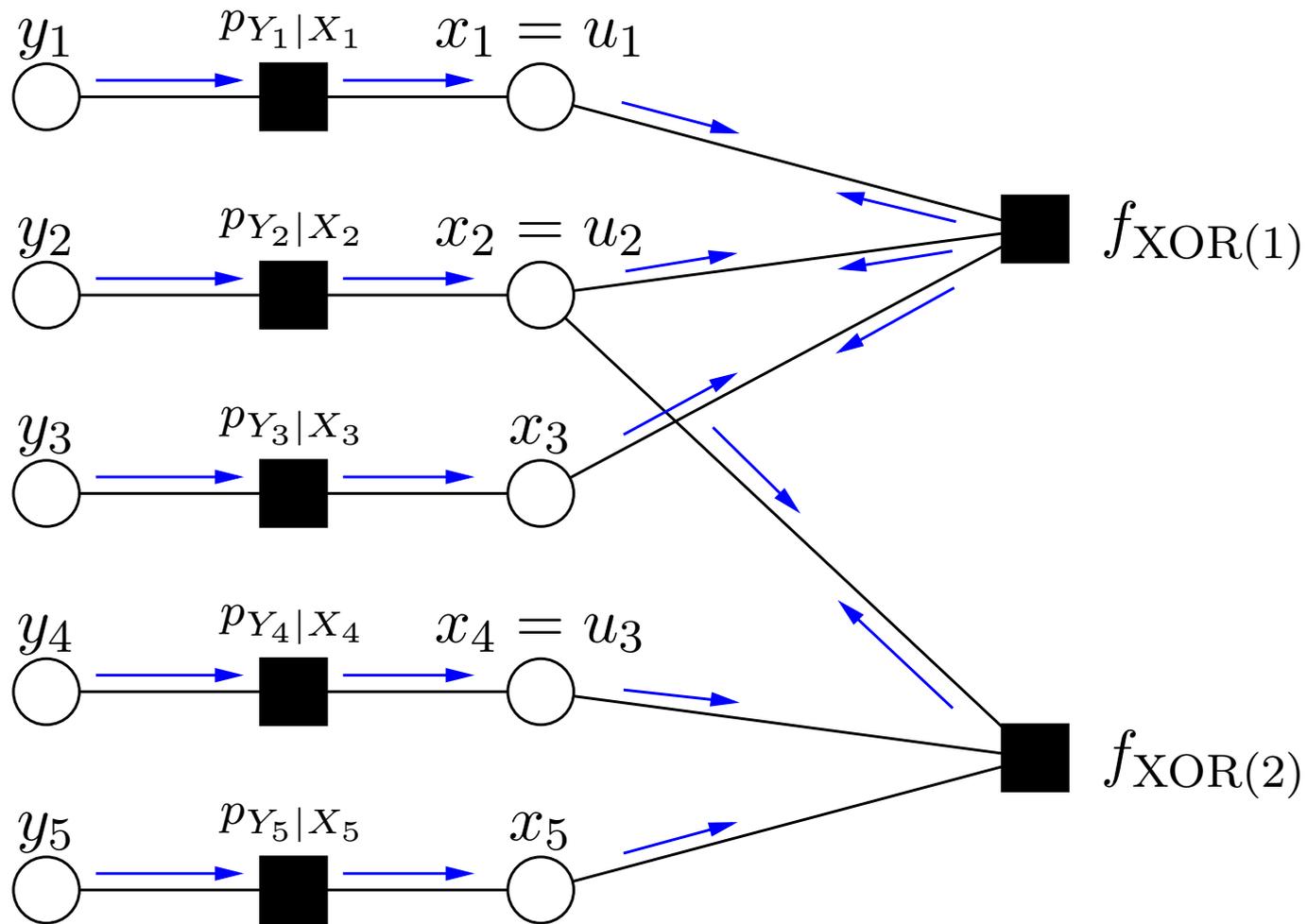
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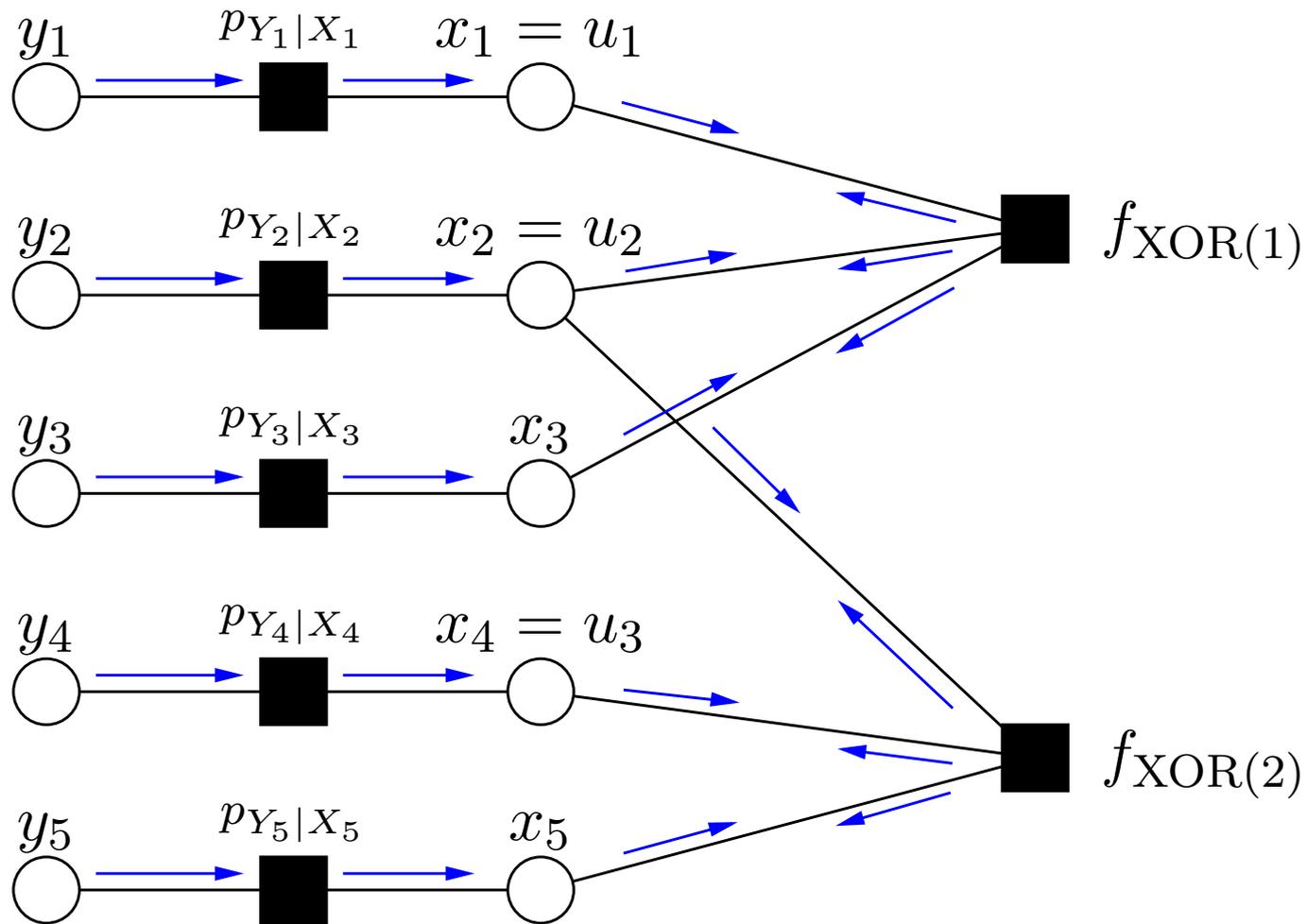
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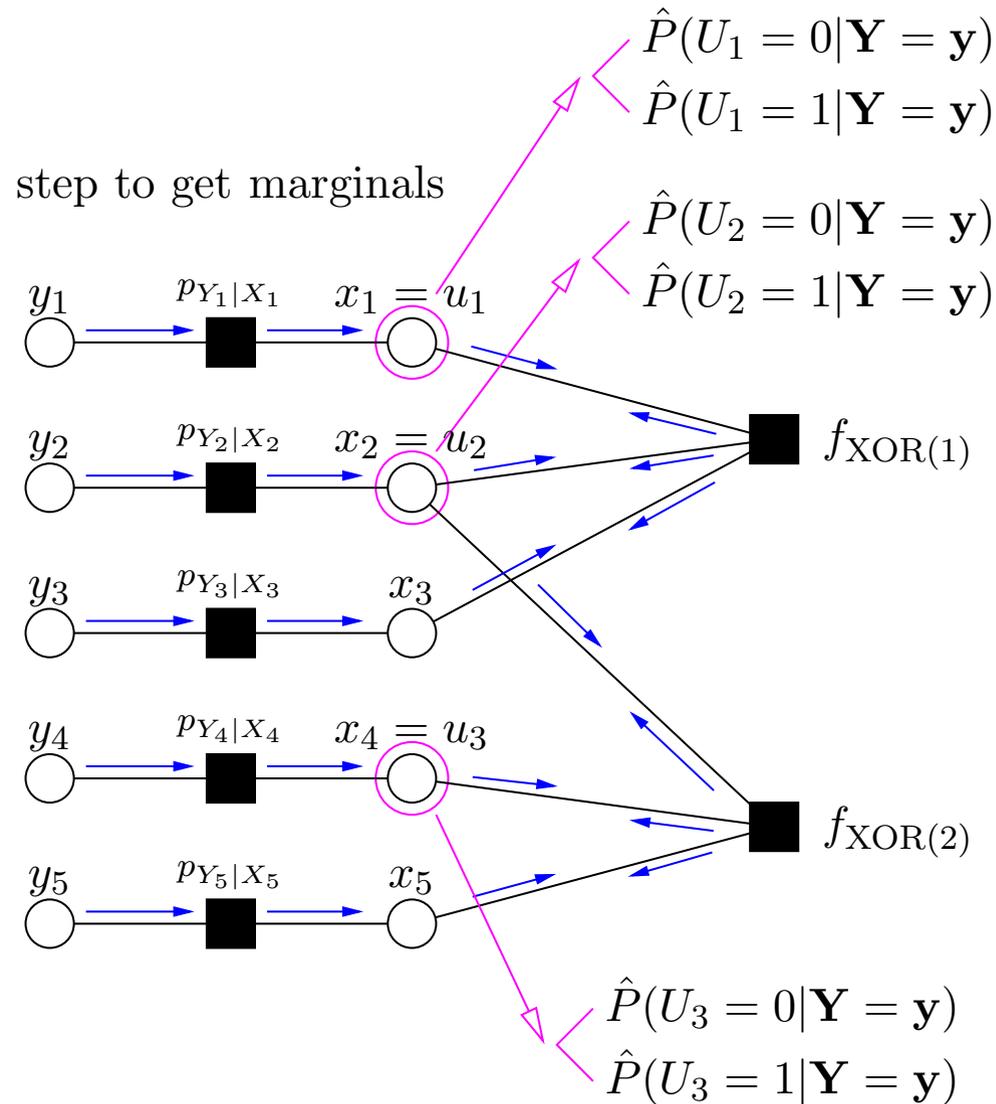
SPA Decoding (Factor graph without cycles)



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SPA Decoding (Factor graph without cycles)



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$$\hat{u}_i^{\text{symbol}}(\mathbf{y}) = \underbrace{\operatorname{argmax}_{u_i \in \mathcal{U}}}_{\text{Decision taking}} \underbrace{\sum_{\substack{\mathbf{u} \in \mathcal{U}^k, \mathbf{x} \in \mathcal{X}^n \\ u_i \text{ fixed}}} \underbrace{P_{\mathbf{U}\mathbf{X}\mathbf{Y}}(\mathbf{u}, \mathbf{x}, \mathbf{y})}_{\text{Joint pmf/pdf}}}_{\text{Marginal function}}$$

Decision about symbol u_i based on symbol-wise decoding

Sum-Product Algorithm Decoding

Sum-product algorithm (SPA) decoding:

$$\hat{u}_i^{\text{symbol}}(\mathbf{y}) \approx \underbrace{\operatorname{argmax}_{u_i \in \mathcal{U}}}_{\text{Decision taking}} \underbrace{\sum_{\substack{\mathbf{u} \in \mathcal{U}^k, \mathbf{x} \in \mathcal{X}^n \\ u_i \text{ fixed}}} \underbrace{P_{\mathbf{U}\mathbf{X}\mathbf{Y}}(\mathbf{u}, \mathbf{x}, \mathbf{y})}_{\text{Joint pmf/pdf}}}_{\text{Marginal function is approximated by Sum-Product Algorithm}}$$

Decision about symbol u_i based on symbol-wise decoding

Sum-Product Algorithm Decoding

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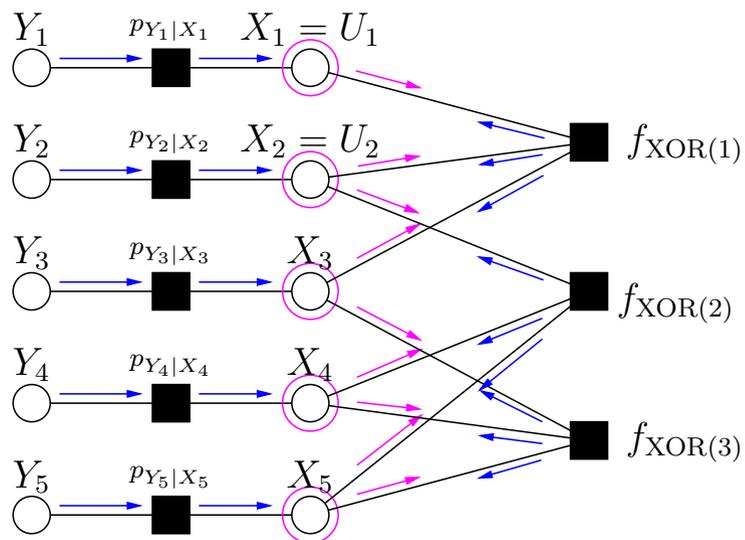
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Decision about symbol u_i based on symbol-wise decoding

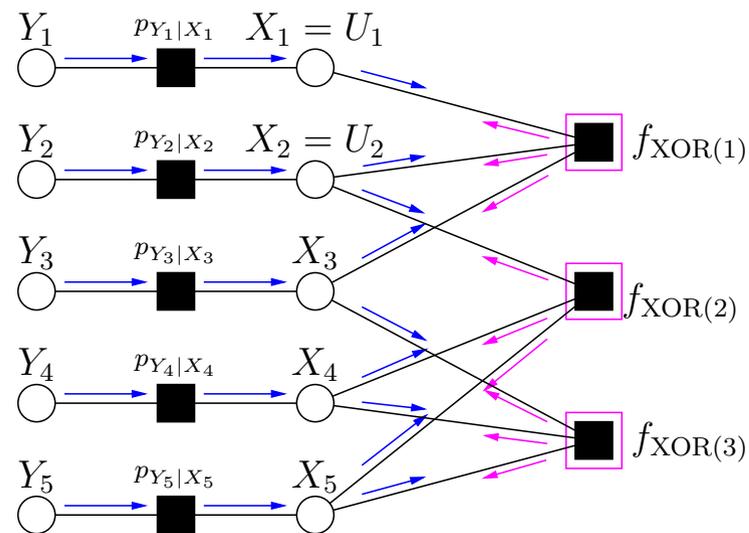
On factor graphs without cycles, the approximation is exact.

SPA Decoding (Factor graph with cycles)

i -th iteration

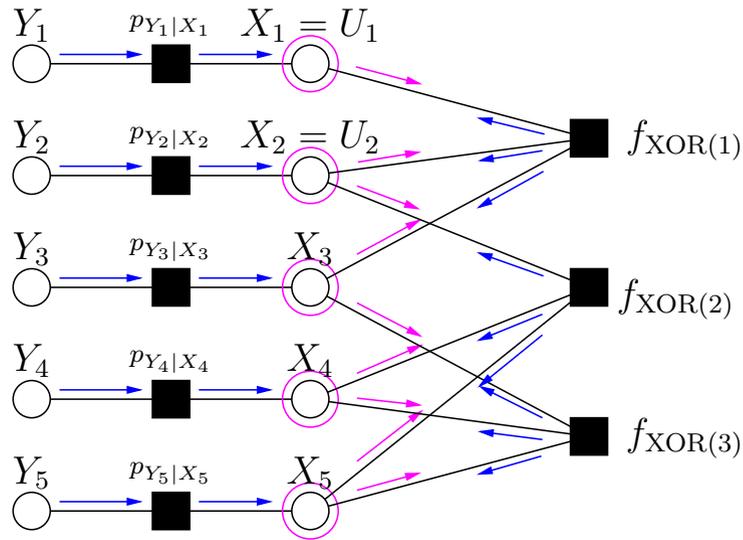


$i.5$ -th iteration

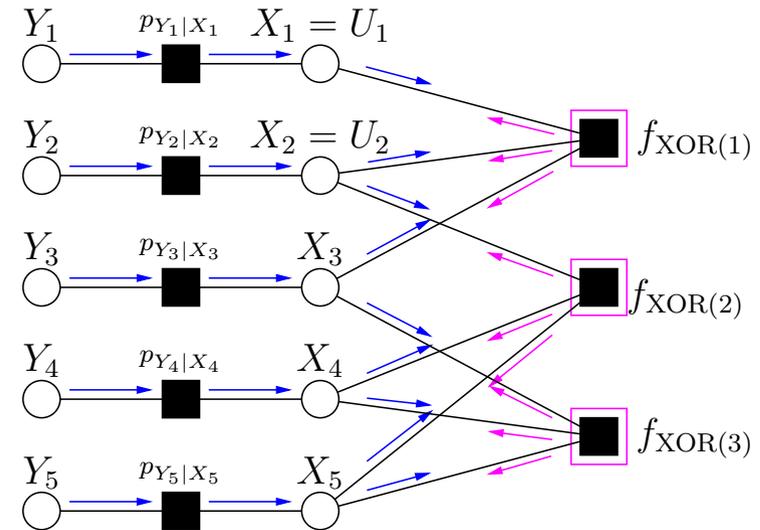


SPA Decoding (Factor graph with cycles)

i -th iteration



$i.5$ -th iteration

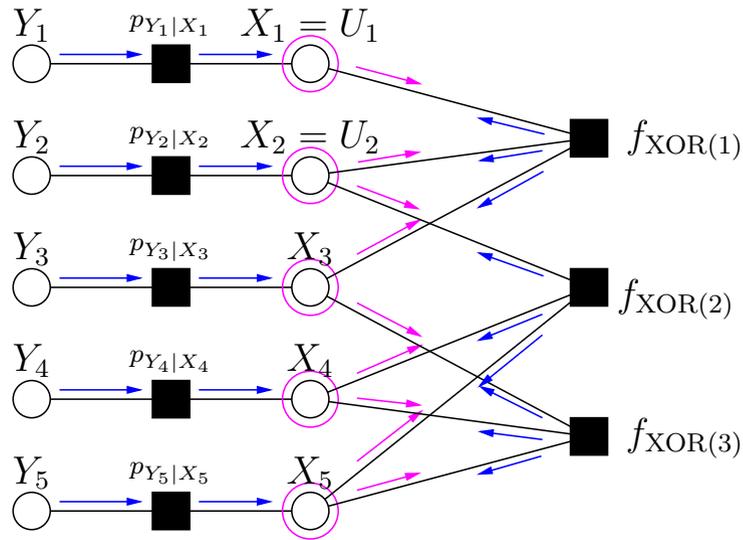


A message-passing algorithm

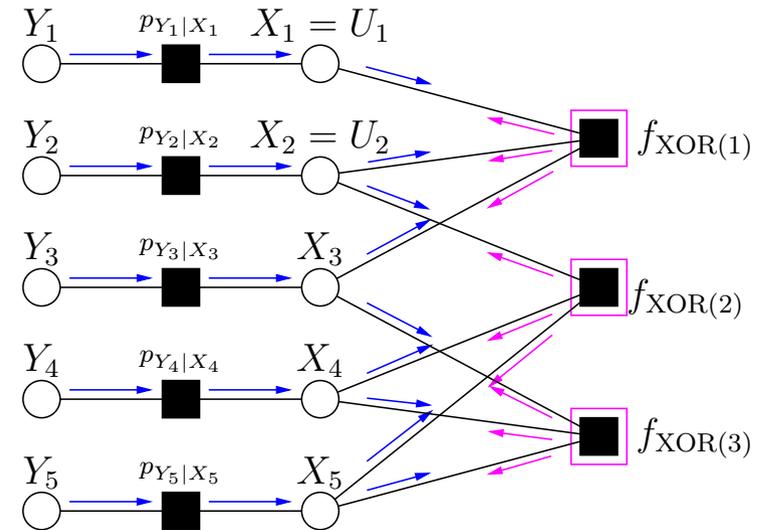
- sends messages along the **edges**,
- does processing of the messages at the **vertices**.

SPA Decoding (Factor graph with cycles)

i -th iteration



$i.5$ -th iteration

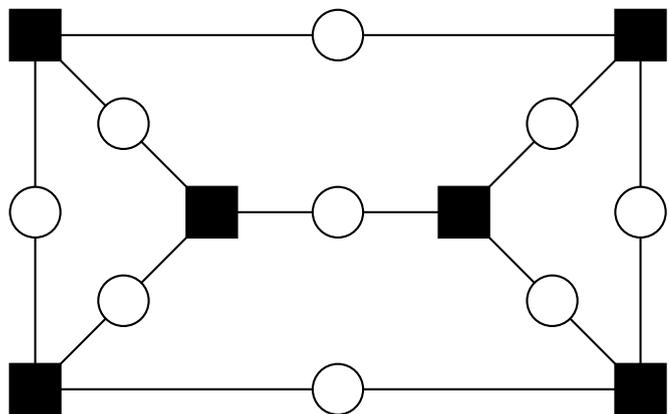


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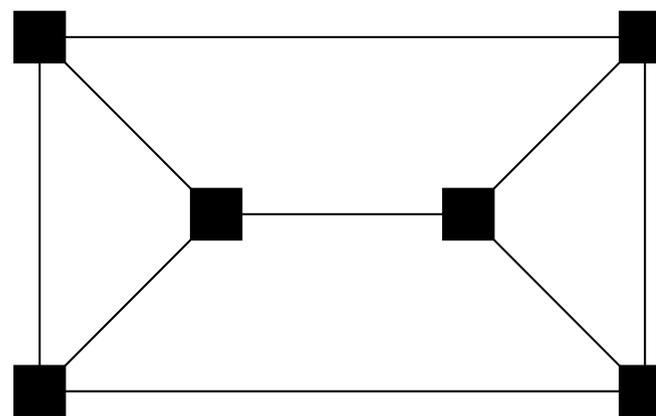
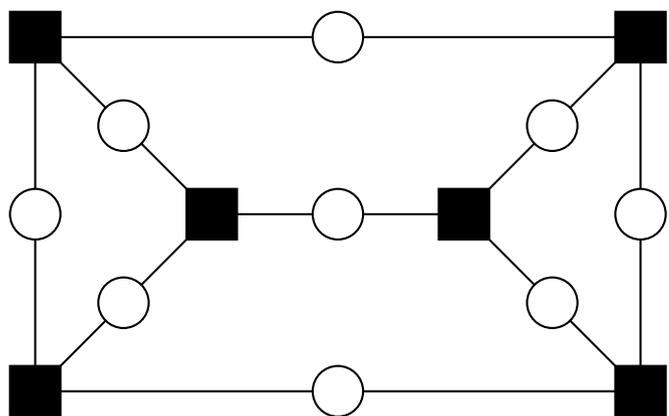
- sends messages along the **edges**,
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Note: all operations are performed **locally**!

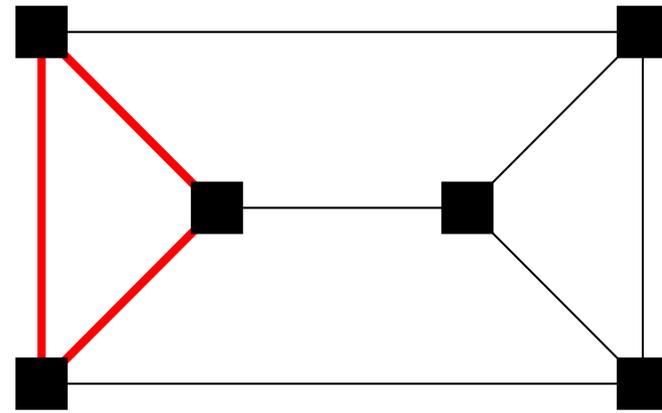
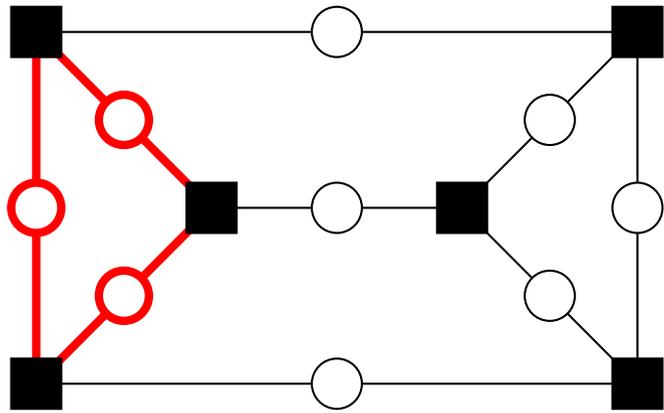
Factor Graph of a Cycle Code



Factor Graph of a Cycle Code

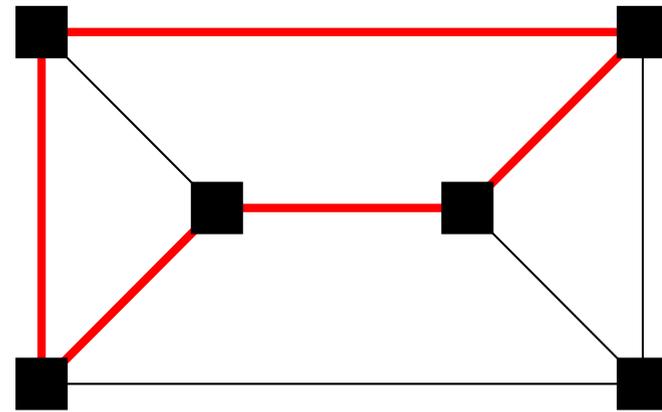
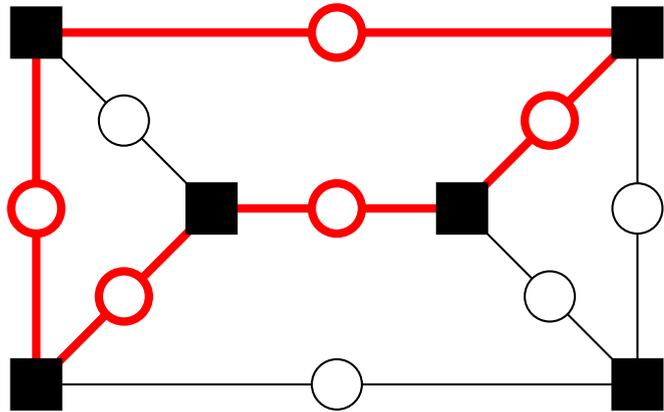


Factor Graph of a Cycle Code



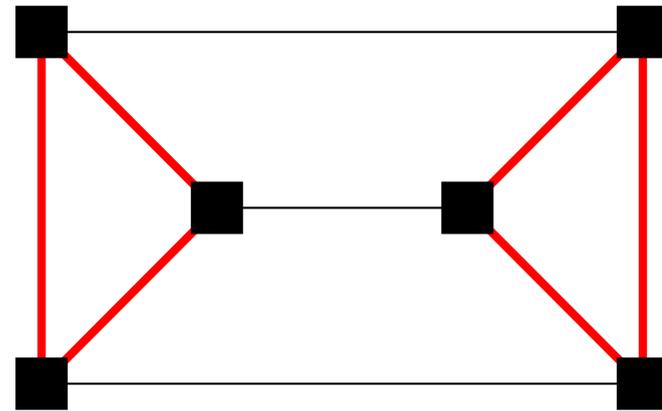
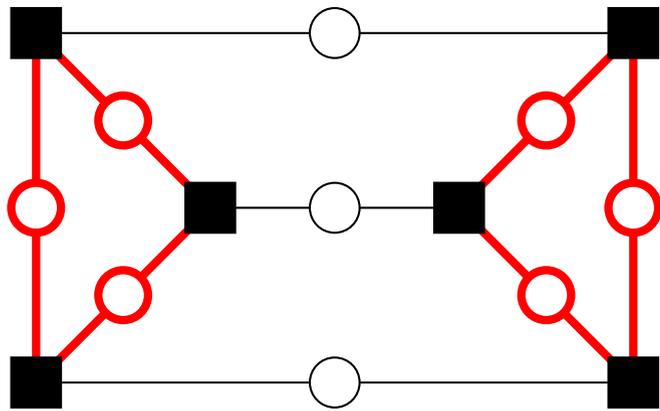
Cycle codes are called cycle codes because codewords correspond to **simple cycles** (or to the **symmetric difference set of simple cycles**) in the Tanner/factor graph.

Factor Graph of a Cycle Code

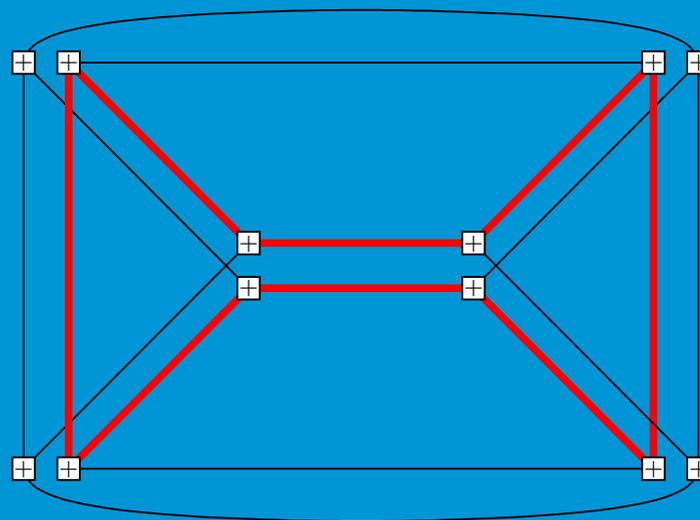
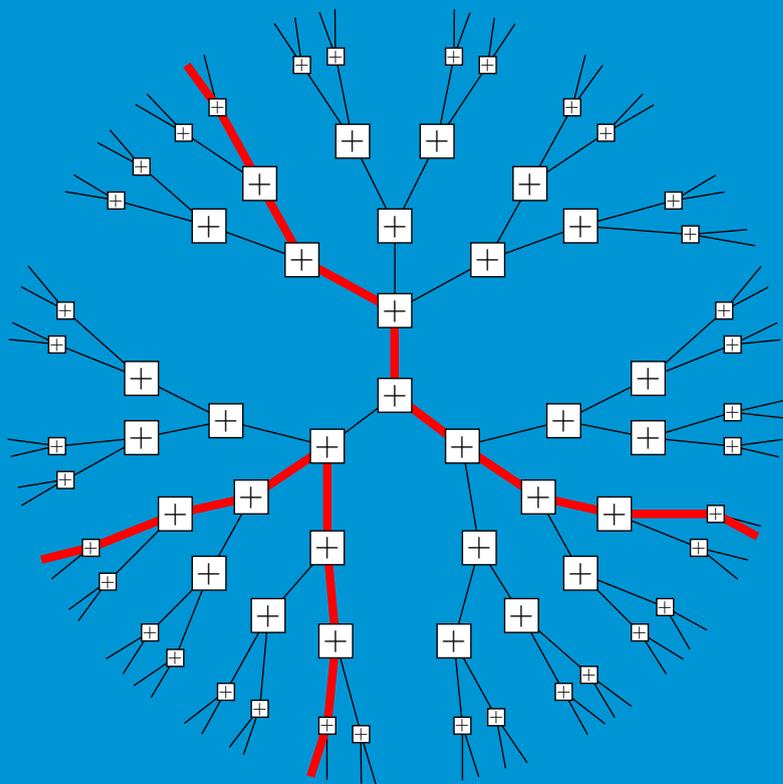
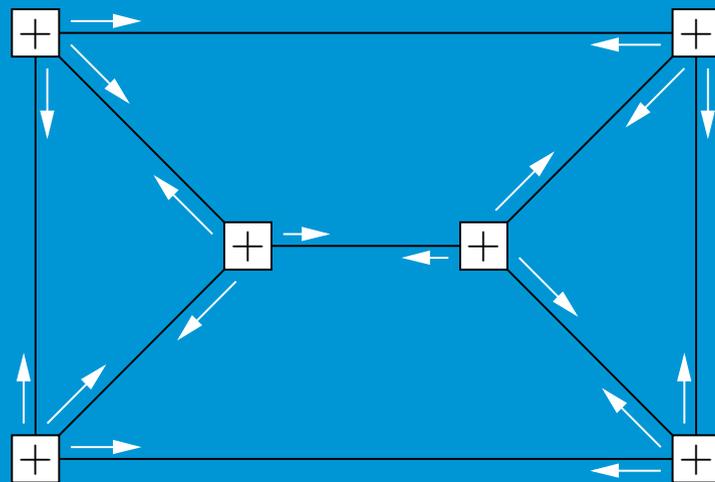


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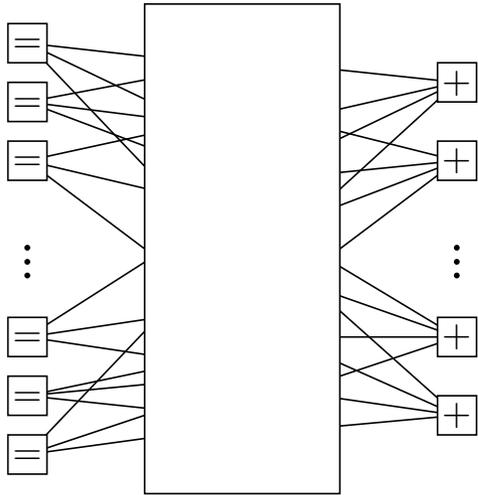


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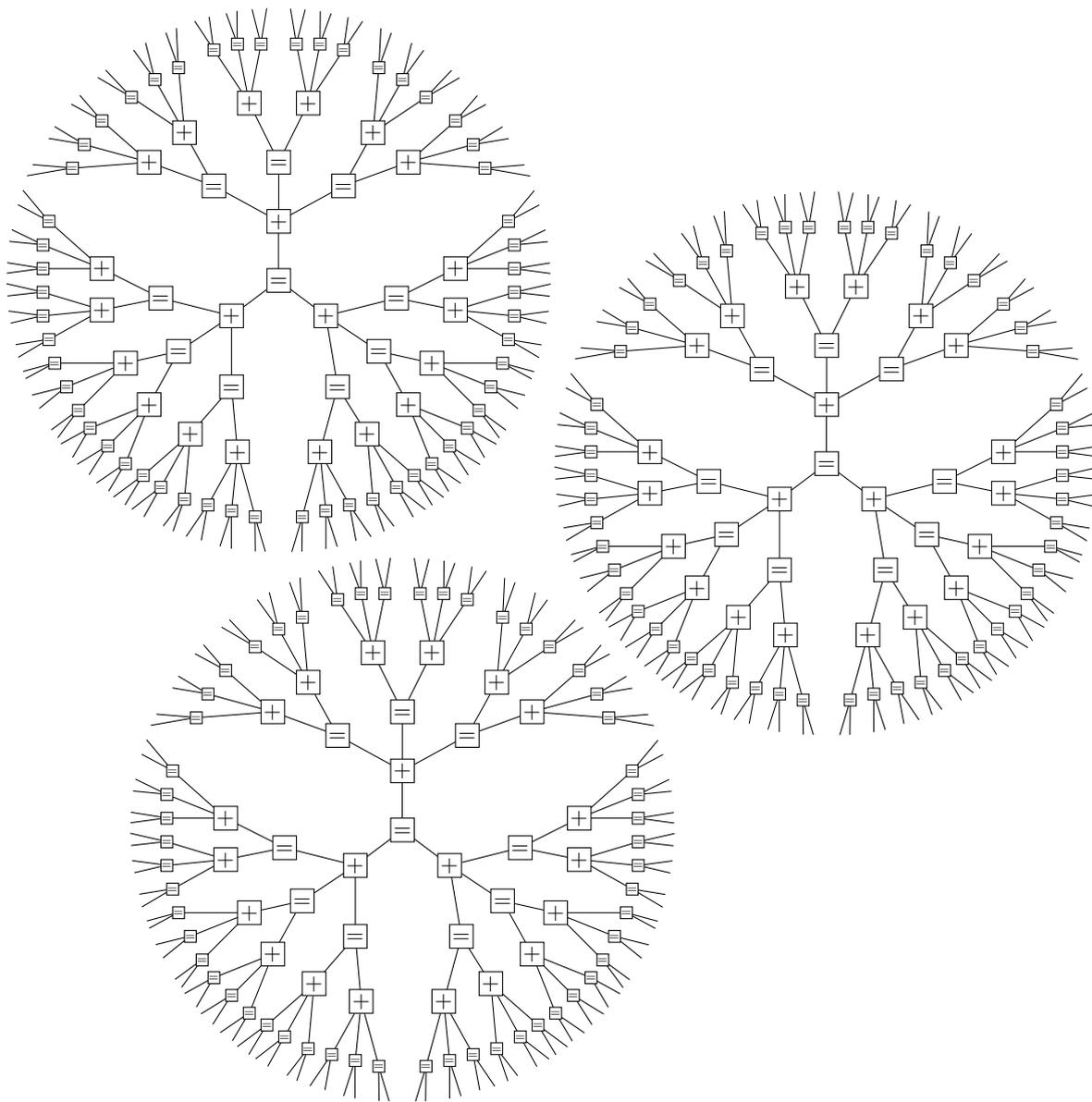
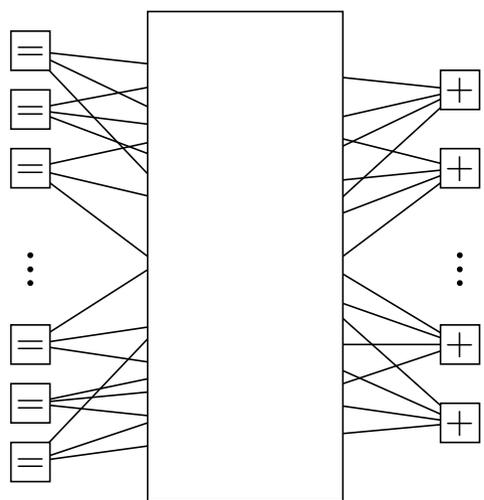


$$\zeta(V_1, \dots, V_n) = \sum_{\mathbf{k}} \zeta_{\mathbf{k}} \mathbf{V}^{\mathbf{k}} = \prod_{[\Gamma]} \frac{1}{1 - g(\Gamma, \mathbf{V})}$$

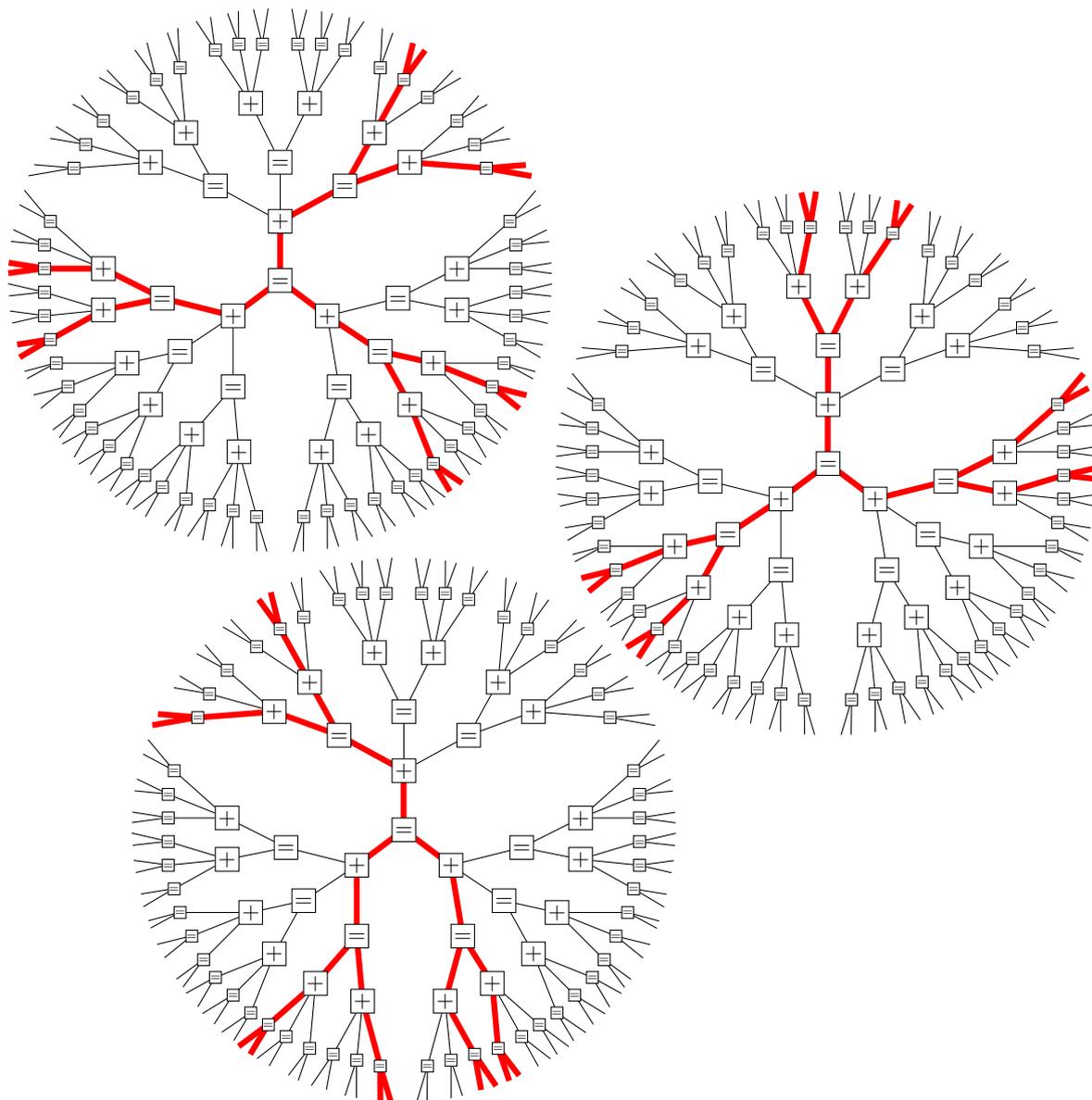
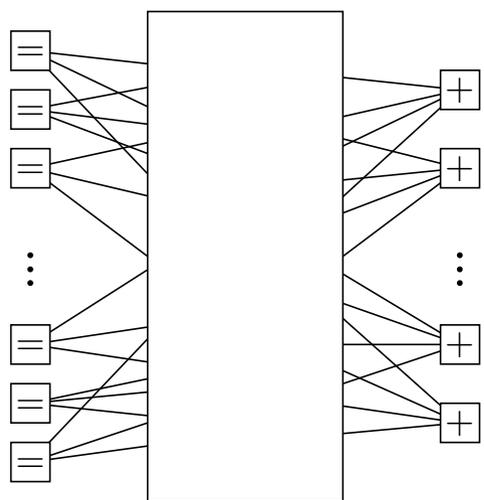
Computation trees

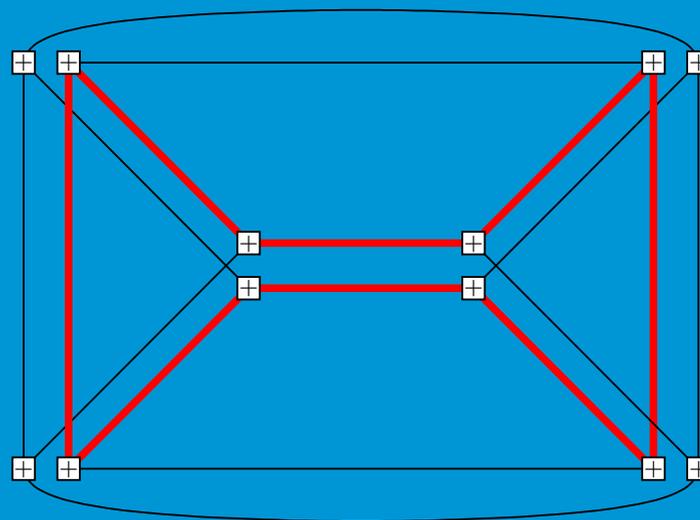
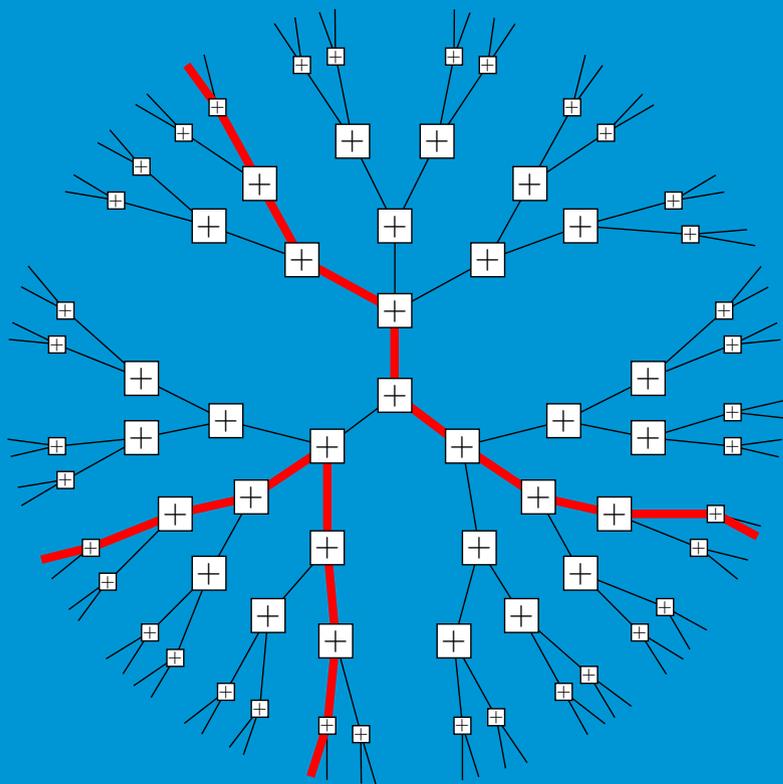
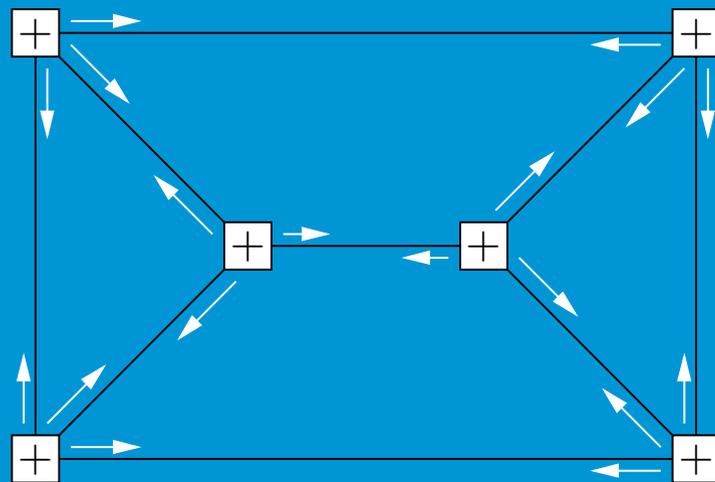


Computation trees



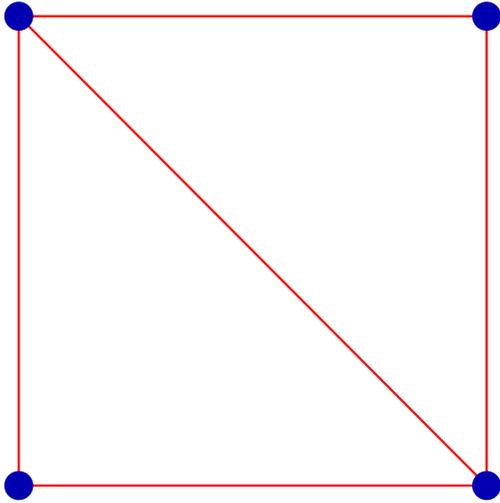
Computation trees





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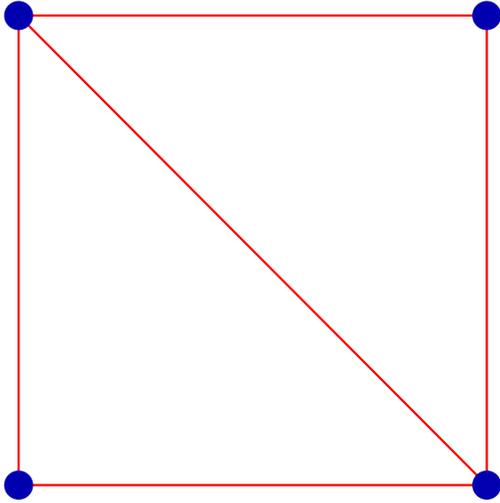
Finite Graph Covers



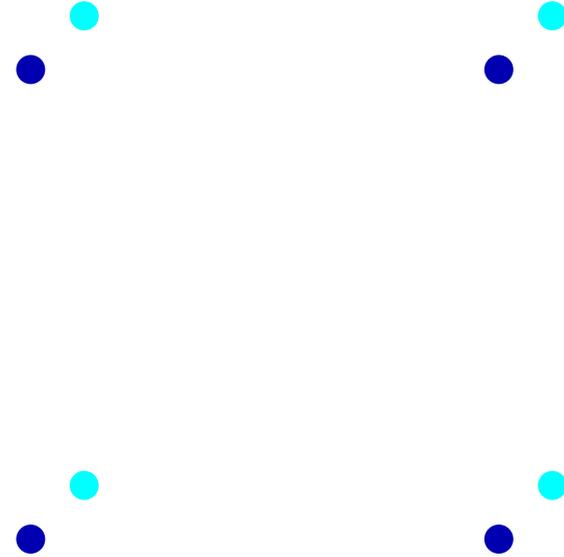
original graph

Definition: A double cover of a graph is ...

Finite Graph Covers



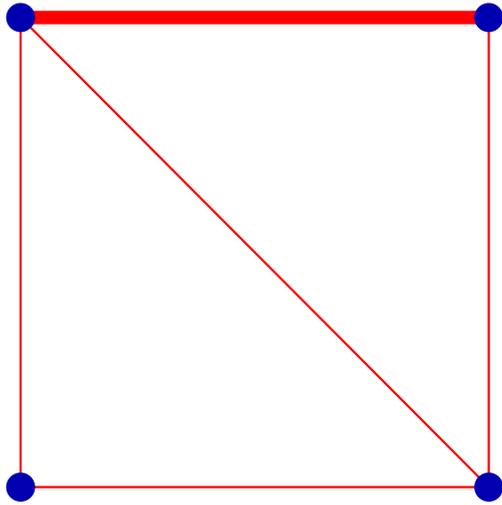
original graph



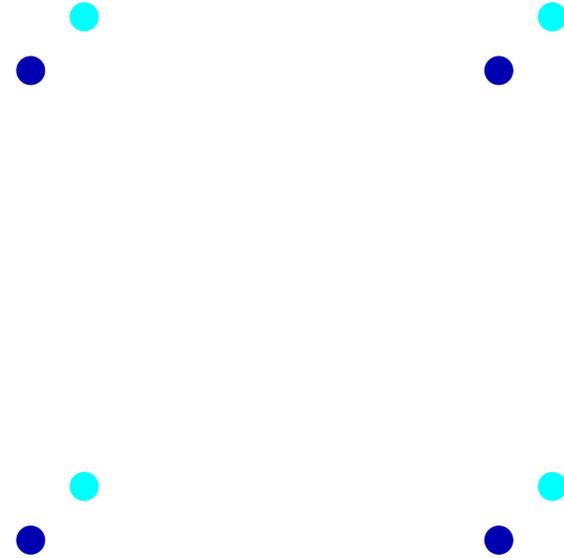
2-fold cover of
original graph

Definition: A double cover of a graph is . . .

Finite Graph Covers



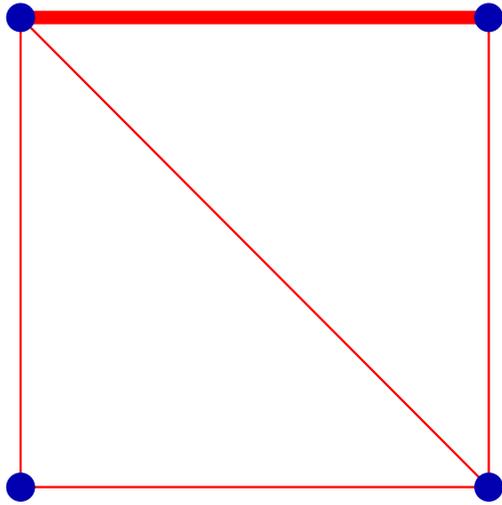
original graph



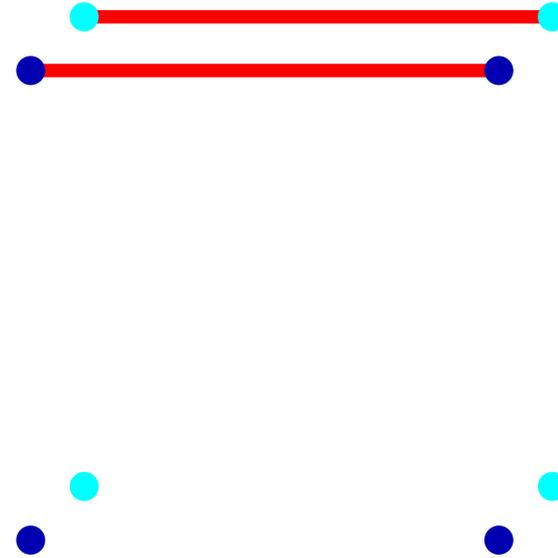
2-fold cover of
original graph

Definition: A double cover of a graph is . . .

Finite Graph Covers



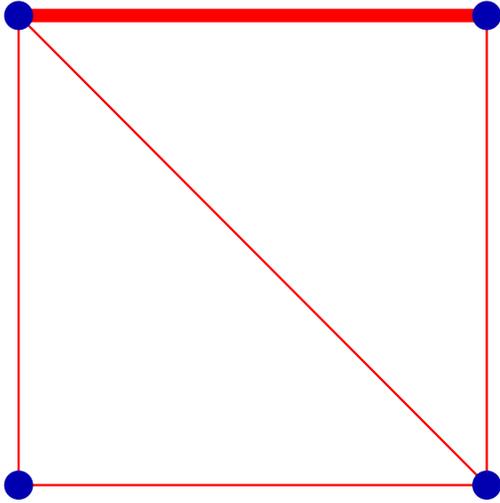
original graph



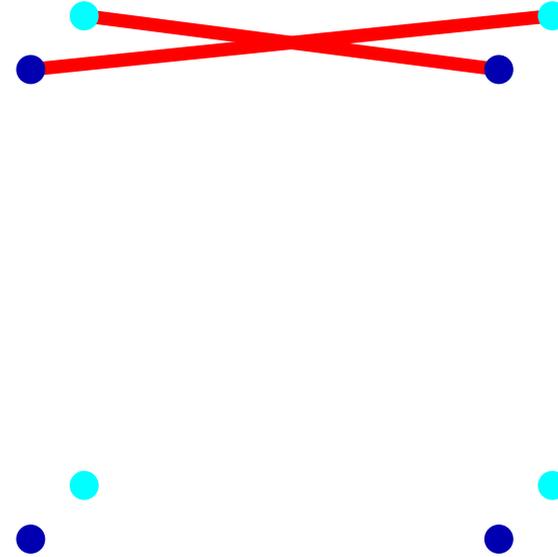
2-fold cover of
original graph

Definition: A double cover of a graph is ...

Finite Graph Covers



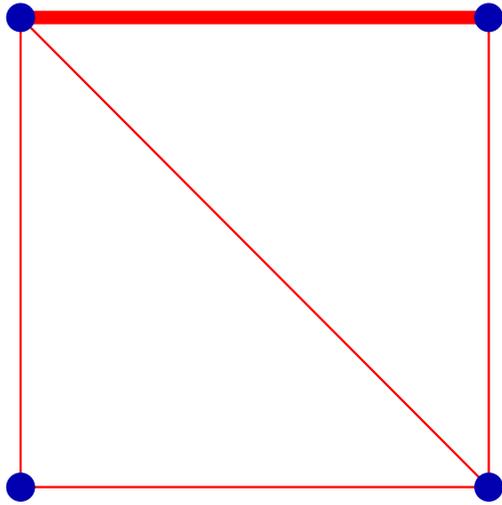
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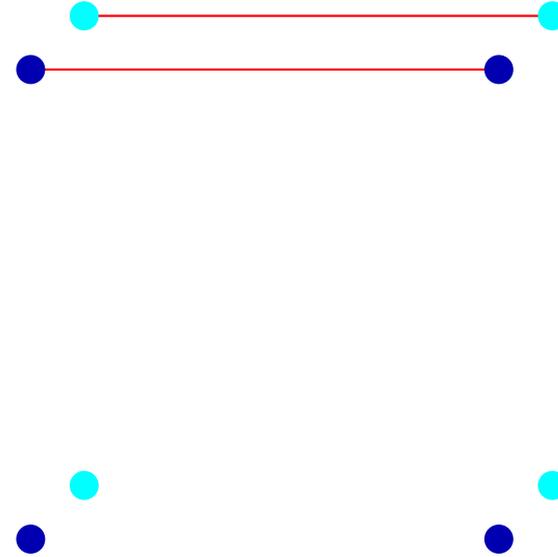
2-fold cover of
original graph

Definition: A double cover of a graph is ...

Finite Graph Covers



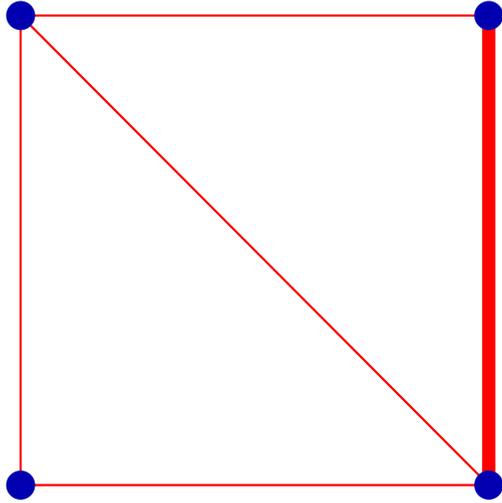
original graph



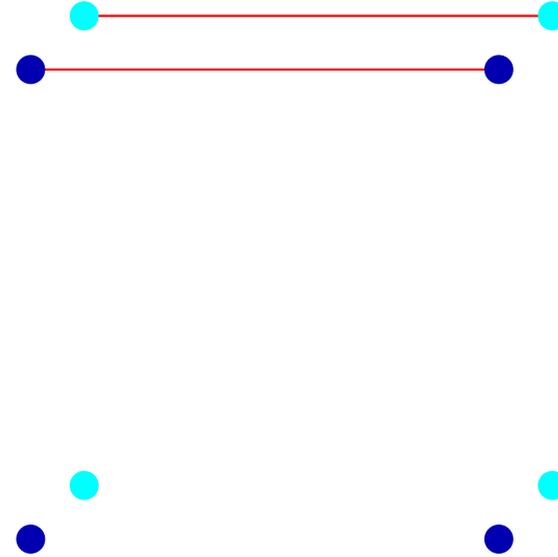
2-fold cover of
original graph

Definition: A double cover of a graph is ...

Finite Graph Covers



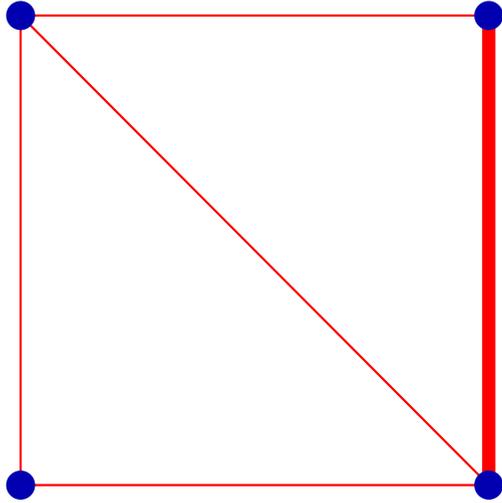
original graph



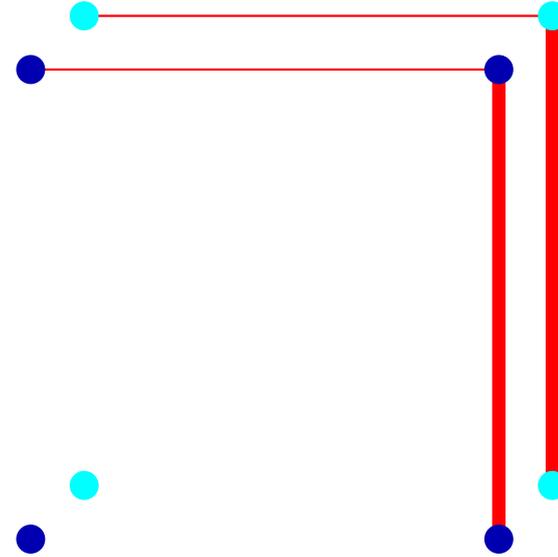
2-fold cover of
original graph

Definition: A double cover of a graph is ...

Finite Graph Covers



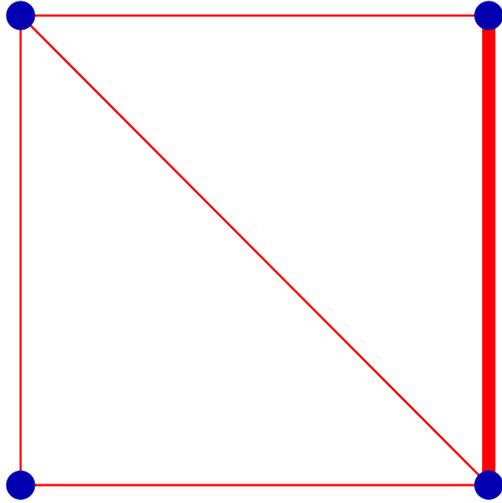
original graph



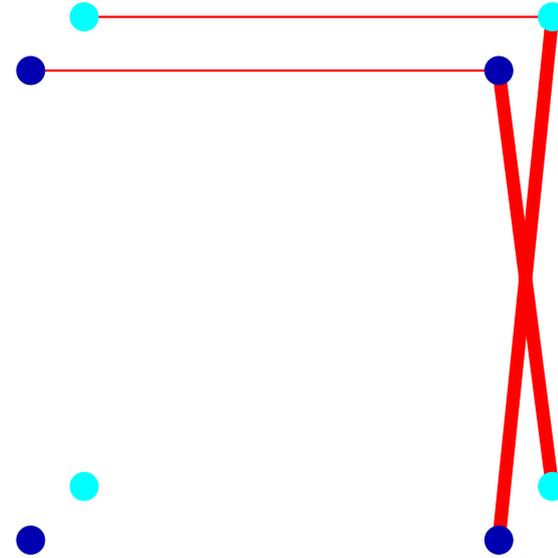
2-fold cover of
original graph

Definition: A double cover of a graph is ...

Finite Graph Covers



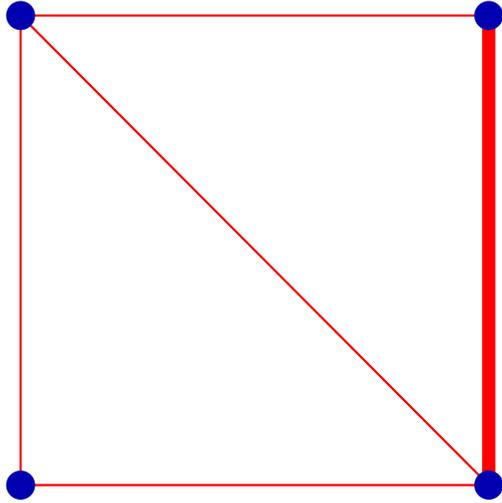
original graph



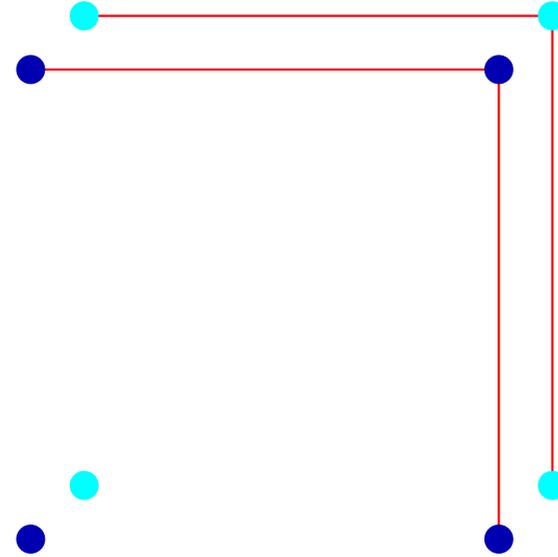
2-fold cover of
original graph

Definition: A double cover of a graph is ...

Finite Graph Covers



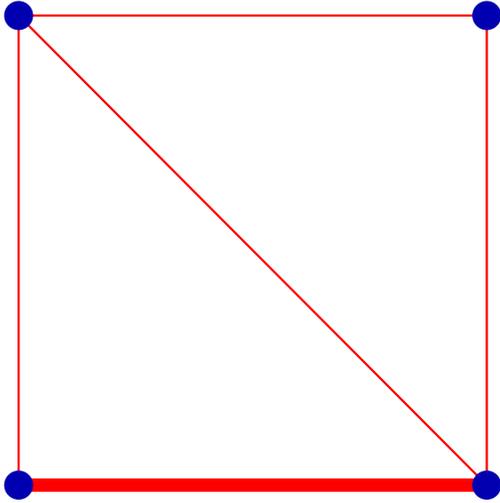
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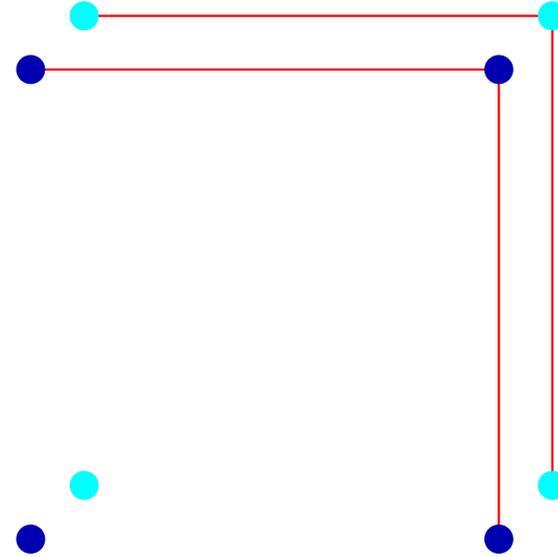
2-fold cover of
original graph

Definition: A double cover of a graph is ...

Finite Graph Covers



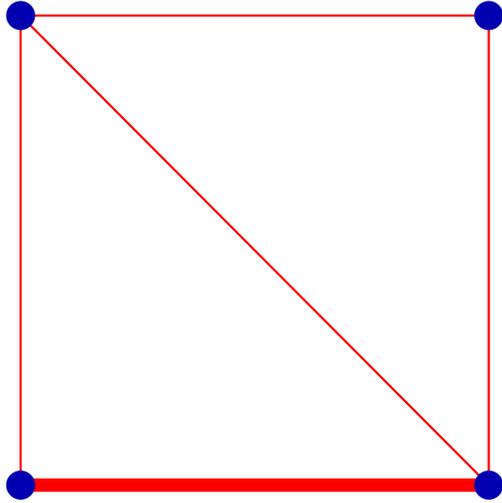
original graph



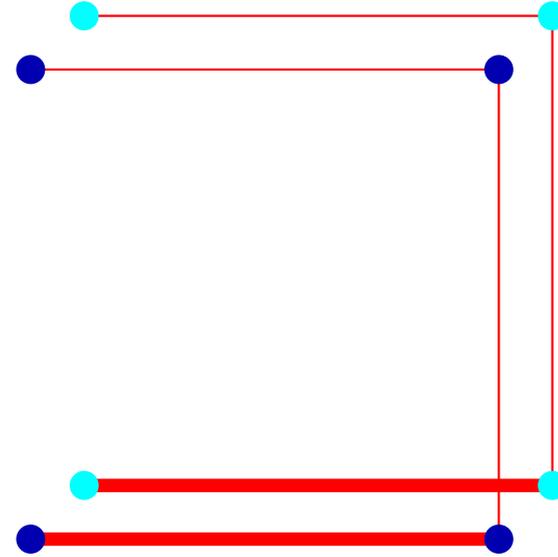
2-fold cover of
original graph

Definition: A double cover of a graph is . . .

Finite Graph Covers



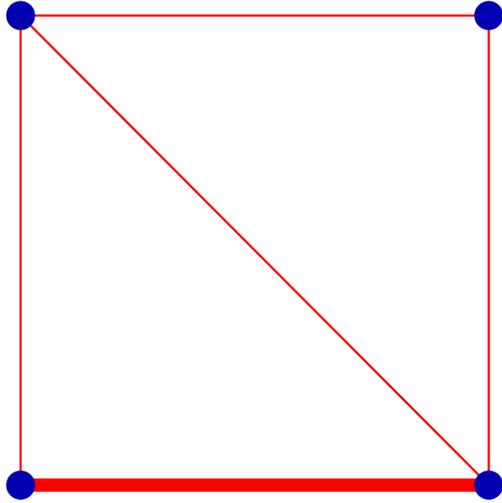
original graph



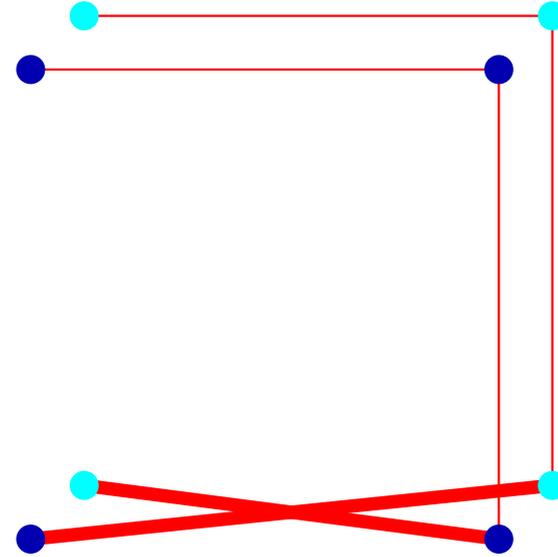
2-fold cover of
original graph

Definition: A double cover of a graph is . . .

Finite Graph Covers



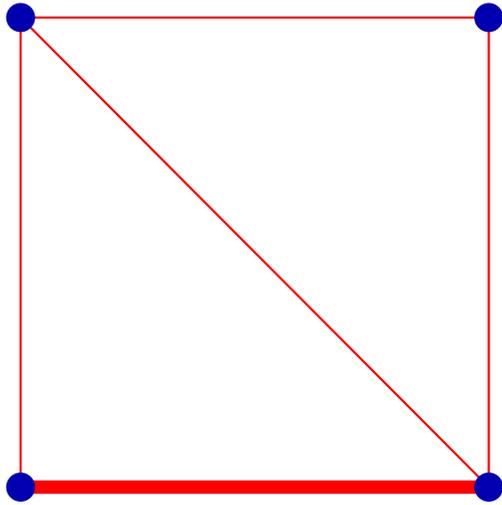
original graph



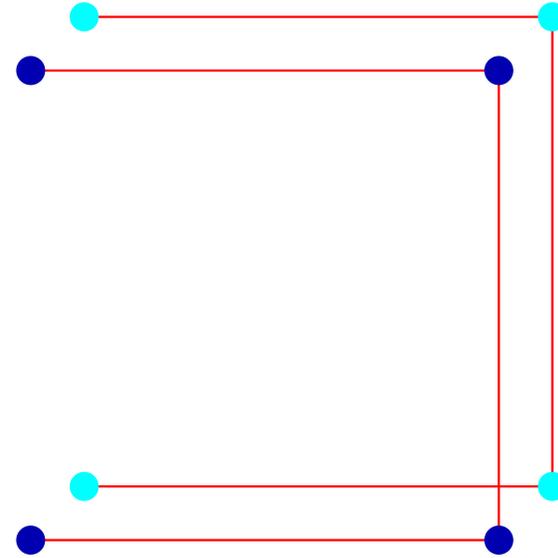
2-fold cover of
original graph

Definition: A double cover of a graph is ...

Finite Graph Covers



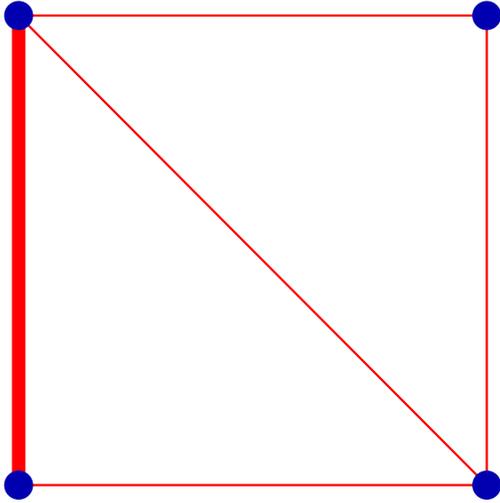
original graph



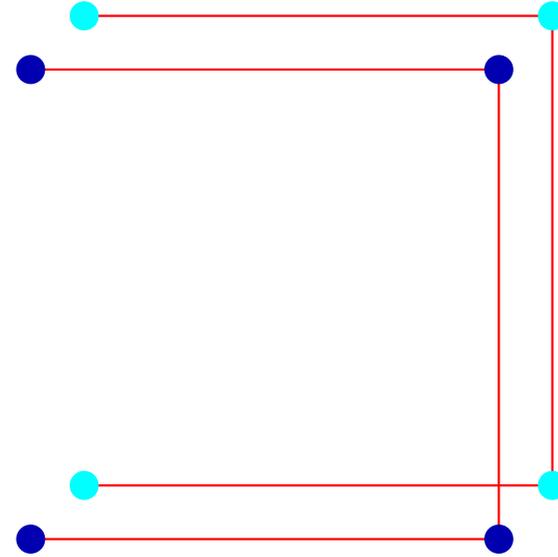
2-fold cover of
original graph

Definition: A double cover of a graph is . . .

Finite Graph Covers



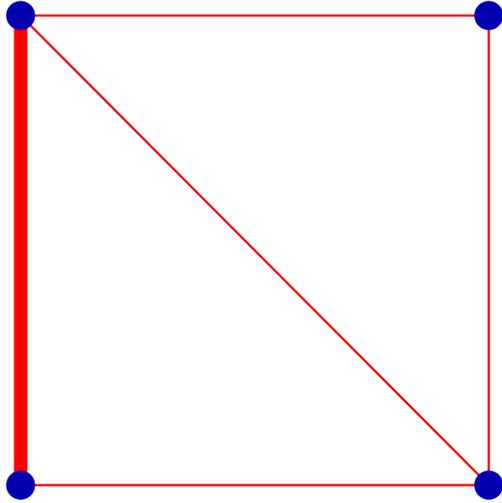
original graph



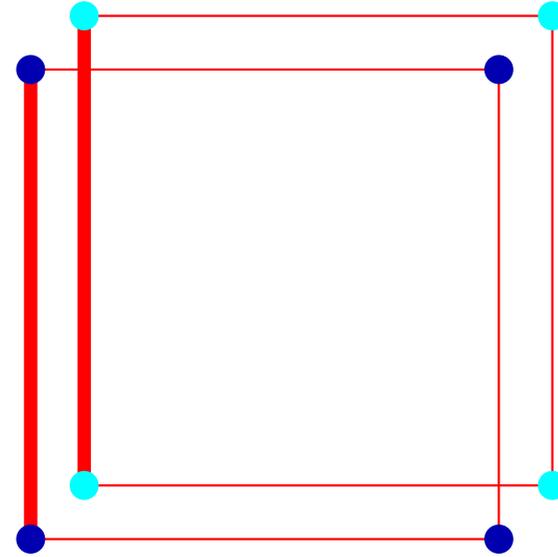
2-fold cover of
original graph

Definition: A double cover of a graph is ...

Finite Graph Covers



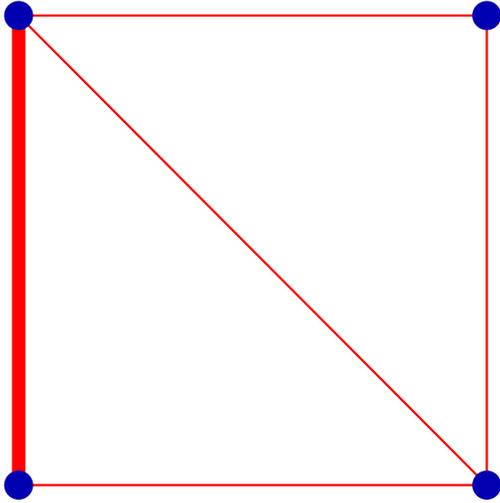
original graph



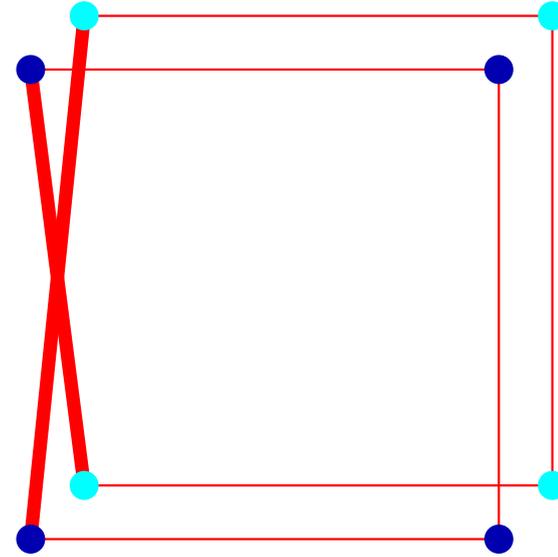
2-fold cover of
original graph

Definition: A double cover of a graph is ...

Finite Graph Covers



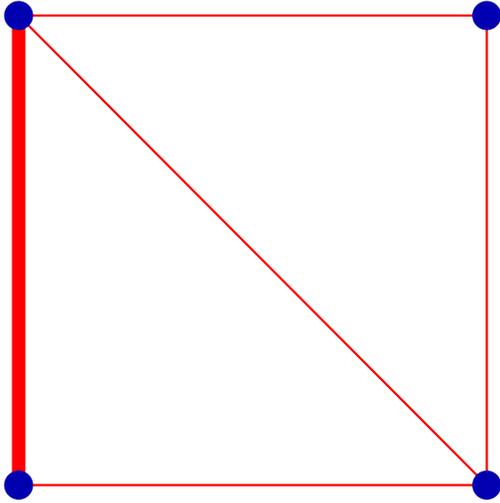
original graph



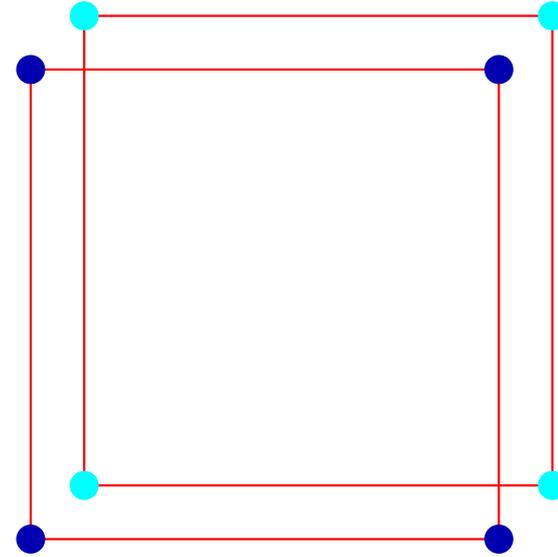
2-fold cover of
original graph

Definition: A double cover of a graph is ...

Finite Graph Covers



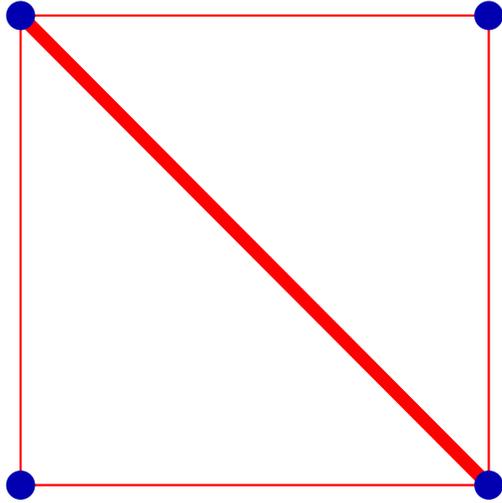
original graph



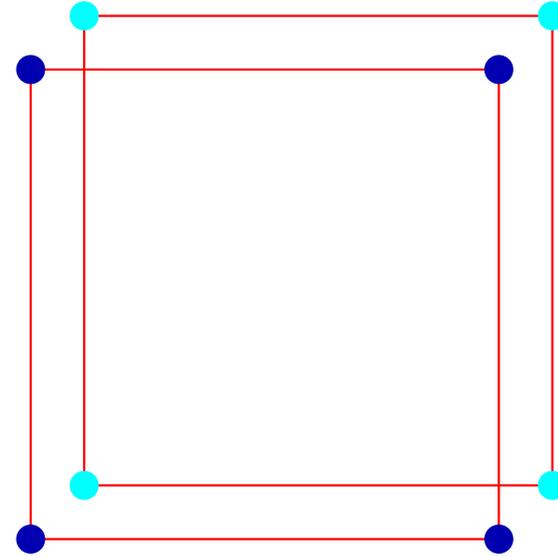
2-fold cover of
original graph

Definition: A double cover of a graph is ...

Finite Graph Covers



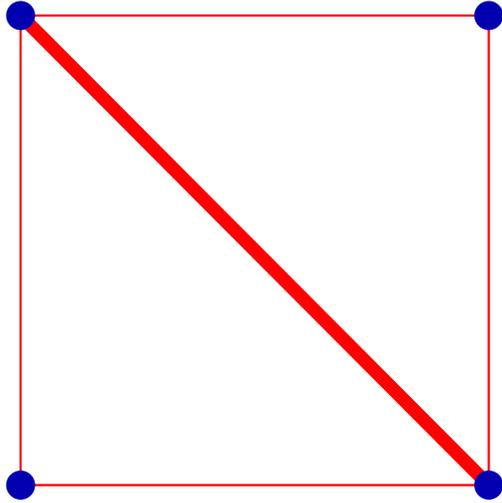
original graph



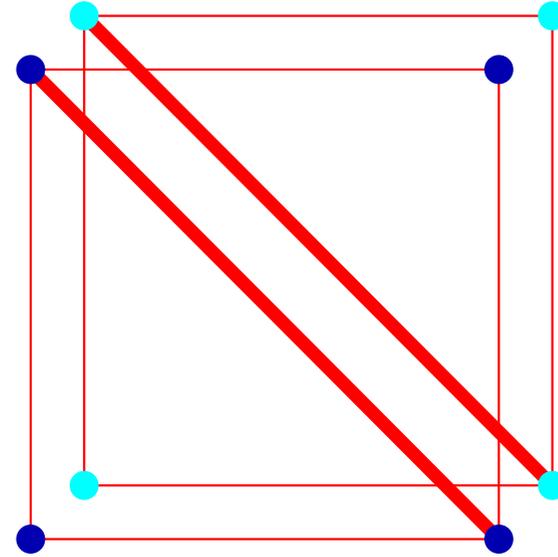
2-fold cover of
original graph

Definition: A double cover of a graph is ...

Finite Graph Covers



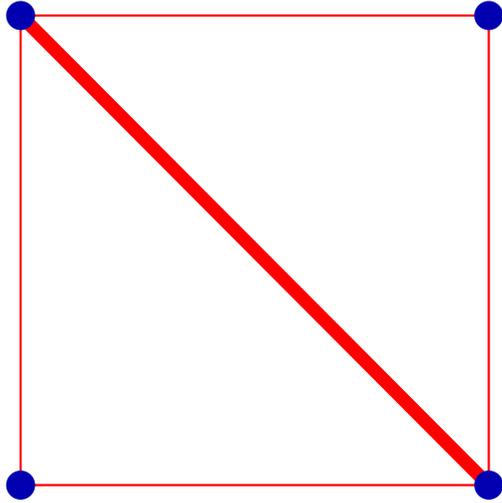
original graph



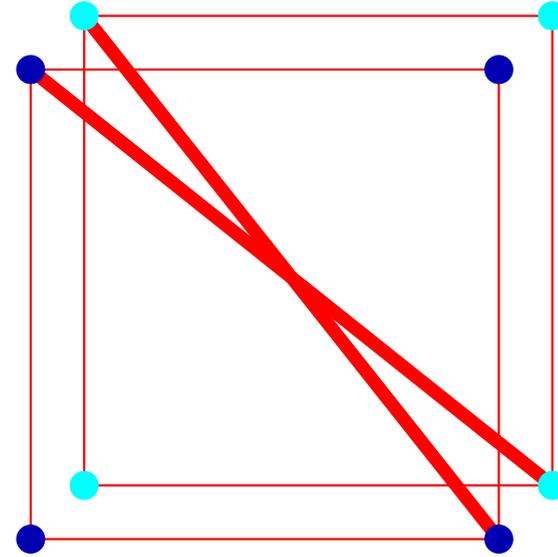
2-fold cover of
original graph

Definition: A double cover of a graph is ...

Finite Graph Covers



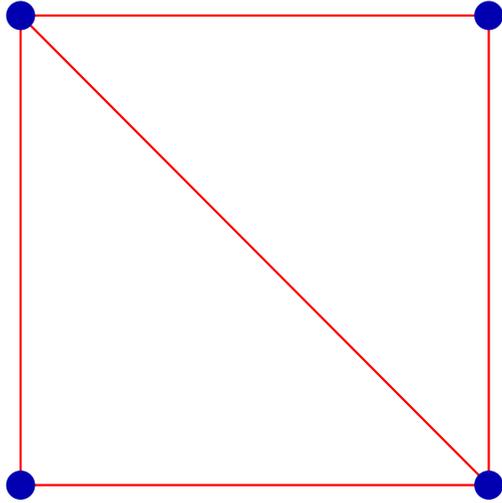
original graph



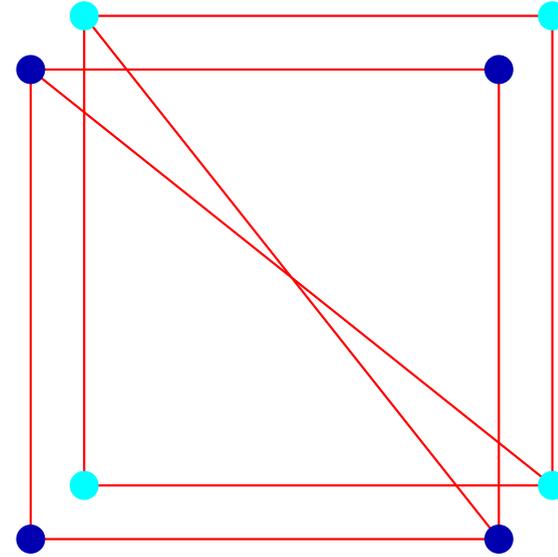
2-fold cover of
original graph

Definition: A double cover of a graph is ...

Finite Graph Covers



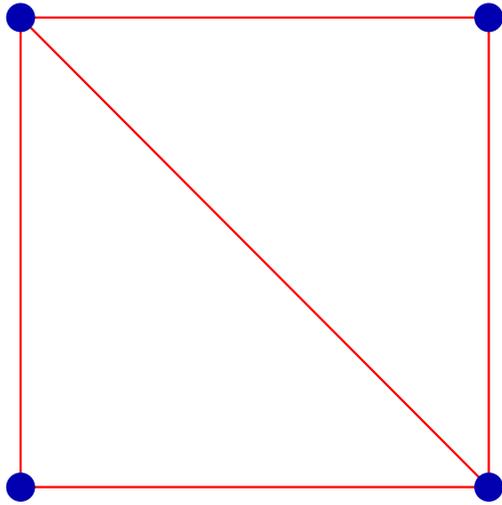
original graph



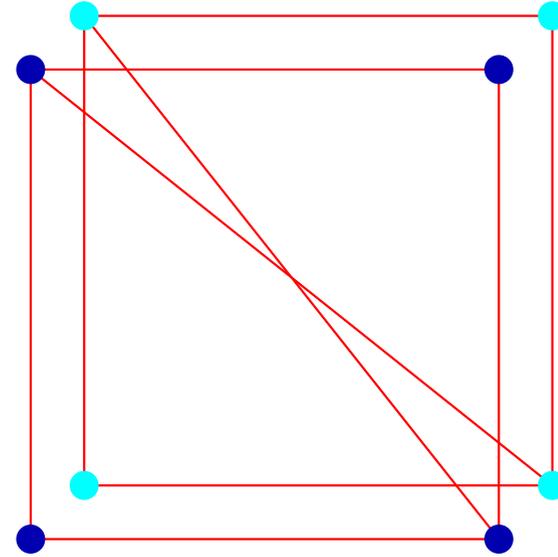
2-fold cover of
original graph

Definition: A double cover of a graph is ...

Finite Graph Covers



original graph

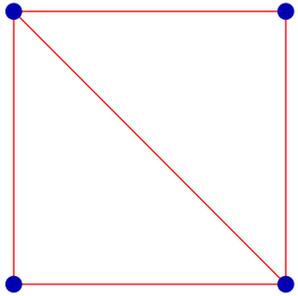


2-fold cover of
original graph

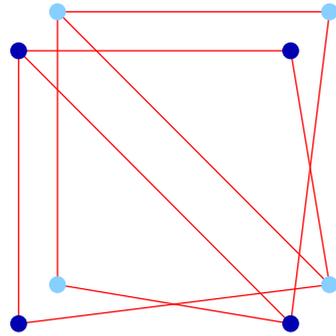
Definition: A double cover of a graph is ...

Note: the above graph has $2! \cdot 2! \cdot 2! \cdot 2! \cdot 2! = (2!)^5$ double covers.

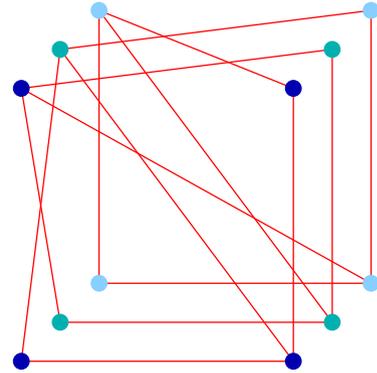
Graph Covers



original graph



(a possible)
double cover of
the original graph

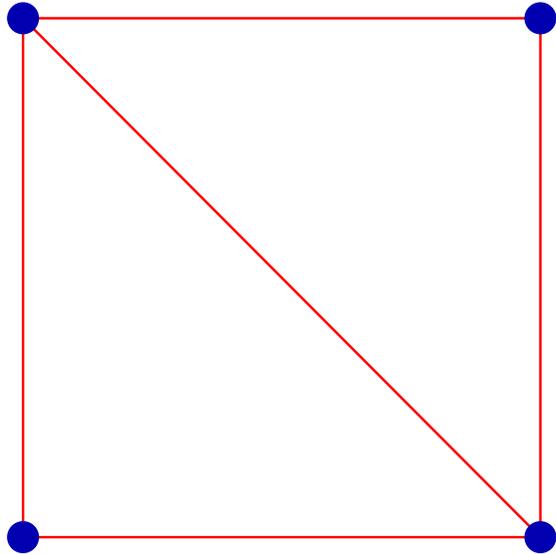


(a possible)
triple cover of
the original graph

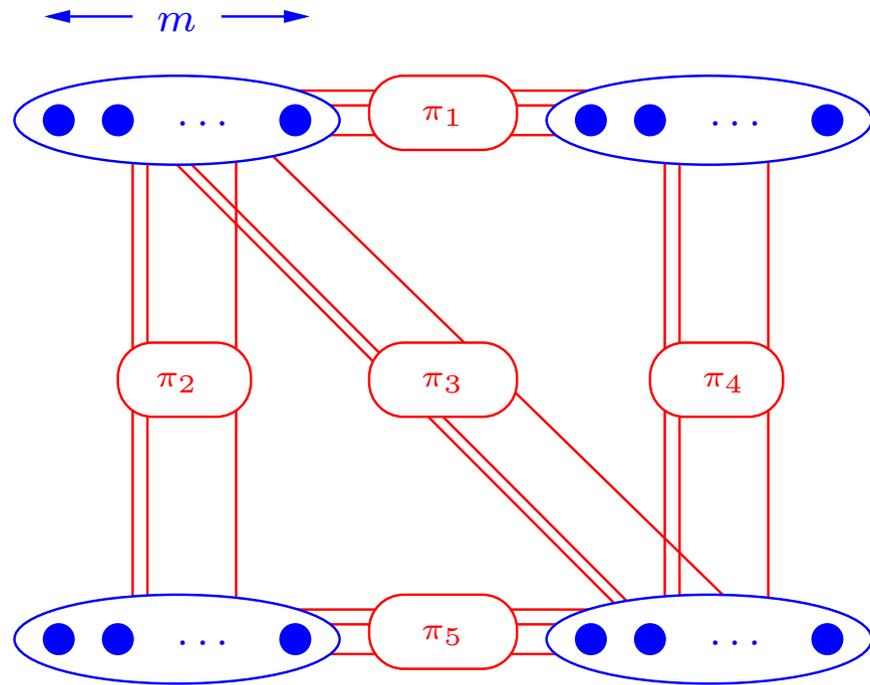
...

Besides **double** covers, a graph also has many **triple** covers, **quadruple** covers, **quintuple** covers, etc.

Graph Covers



original graph



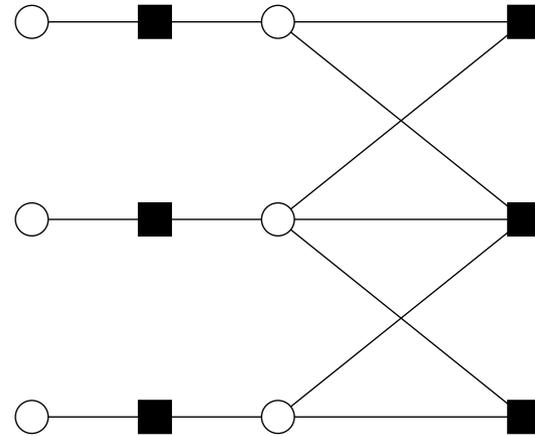
(possible)
 m -fold cover of
original graph

An m -fold cover is also called a cover of degree m .

Do not confuse this degree with the degree of a vertex!

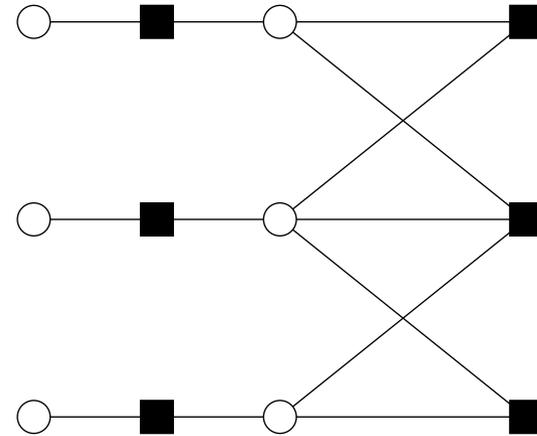
Graph Covers and the Sum-Product Algorithm

Consider this factor graph:

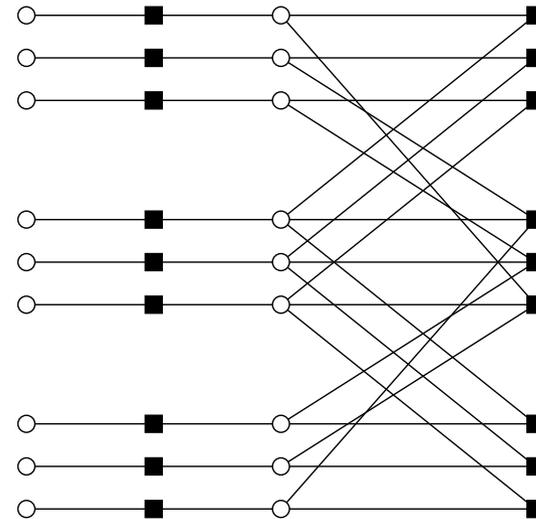


Graph Covers and the Sum-Product Algorithm

Consider this factor graph:

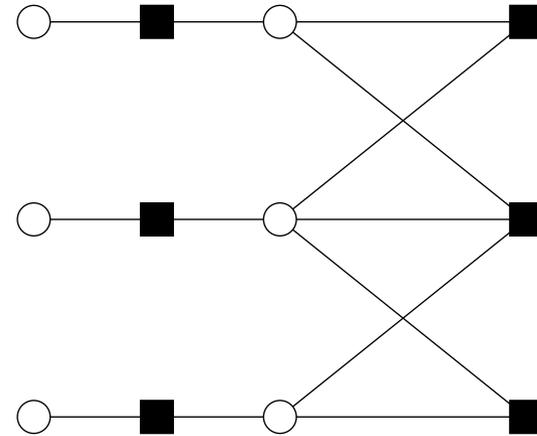


Here is a so-called **triple cover** of the above factor graph:

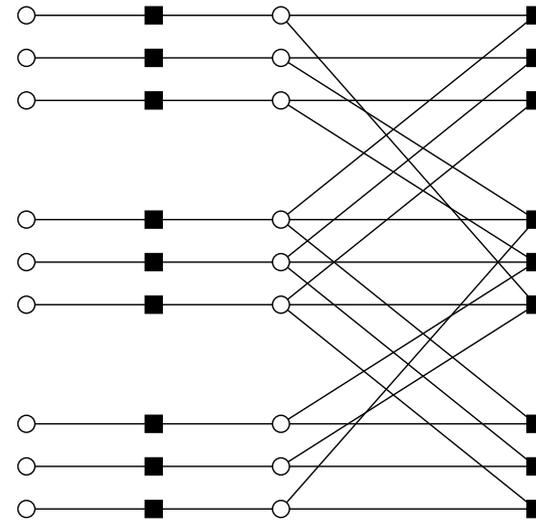


Graph Covers and the Sum-Product Algorithm

Consider this factor graph:



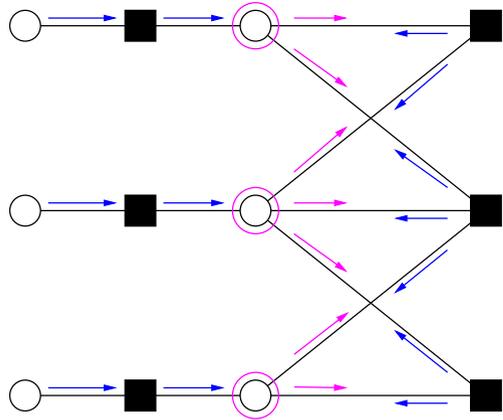
Here is a so-called **triple cover** of the above factor graph:



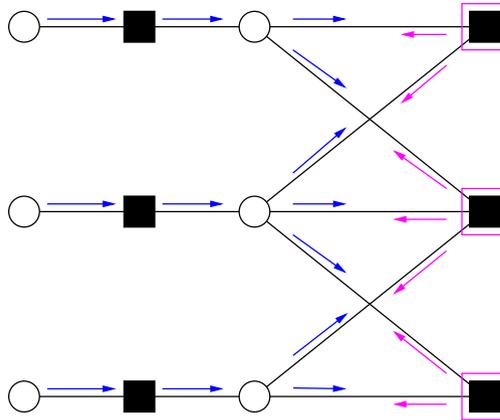
Why do factor graph covers matter?

Graph Covers and the Sum-Product Algorithm

i -th iteration

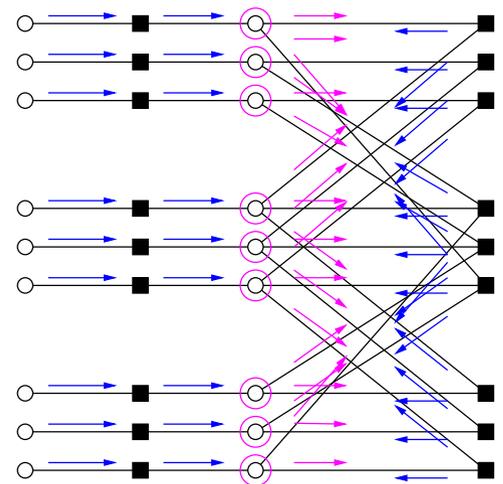
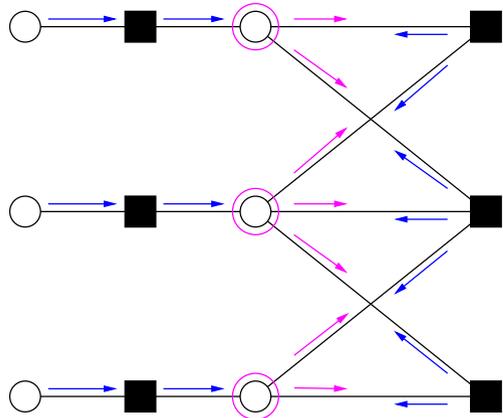


$i.5$ -th iteration

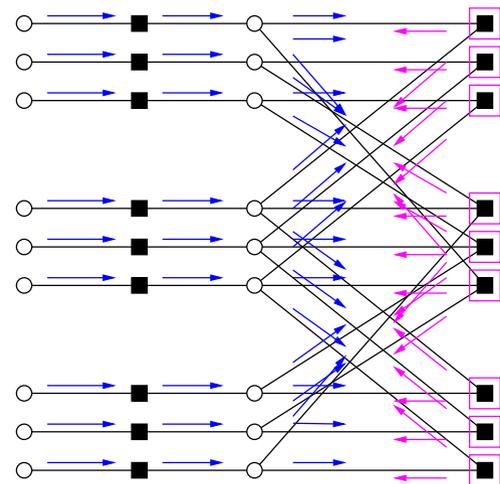
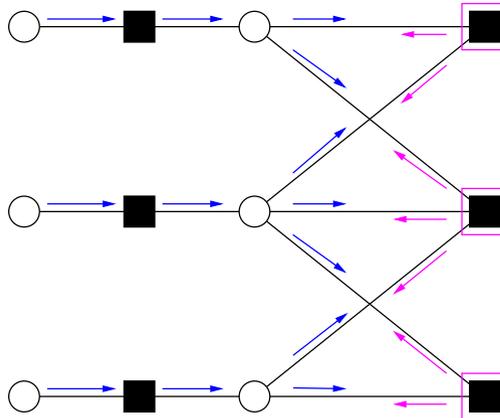


Graph Covers and the Sum-Product Algorithm

i -th iteration

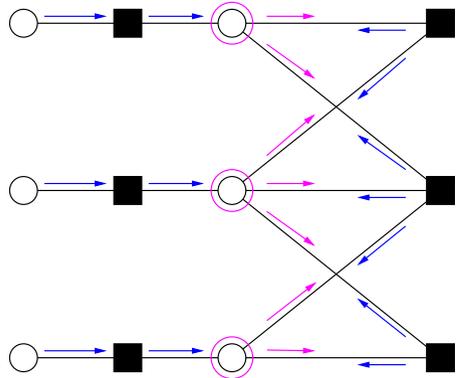


$i.5$ -th iteration

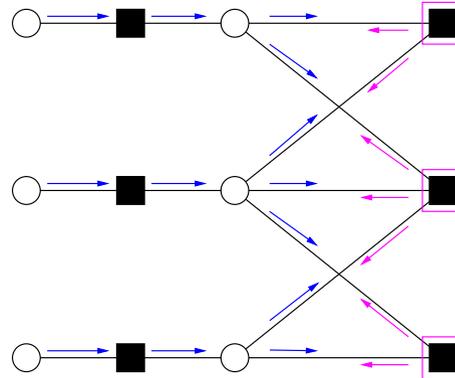


Graph Covers and the Sum-Product Algorithm

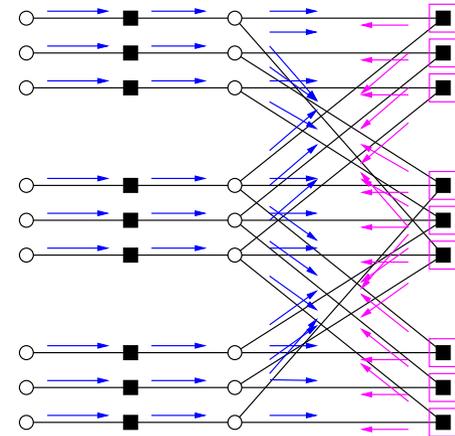
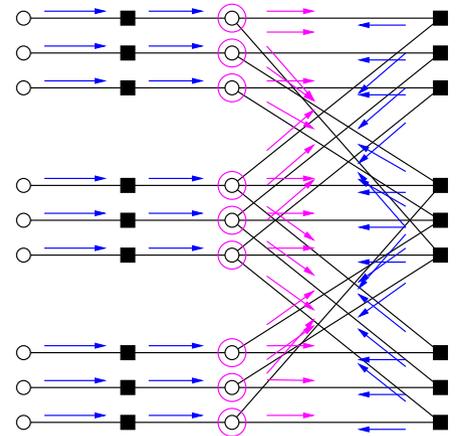
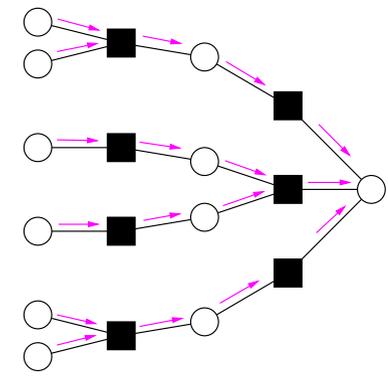
i -th iteration



$i.5$ -th iteration

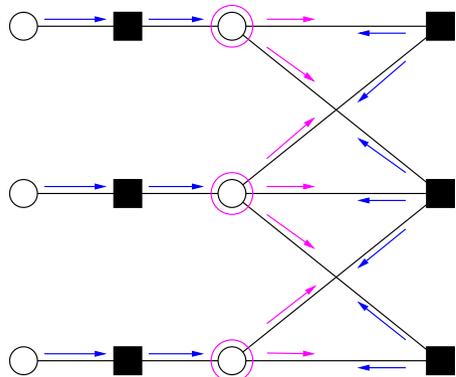


computation tree (without channel function nodes) ...
... where root is bit node 2

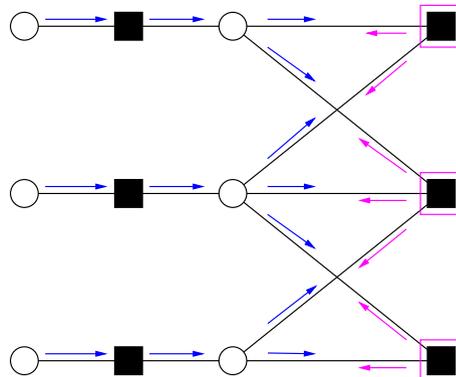


Graph Covers and the Sum-Product Algorithm

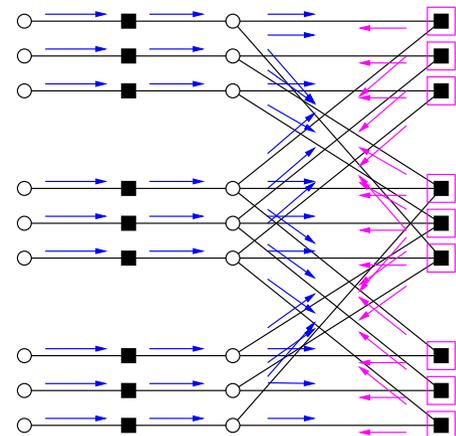
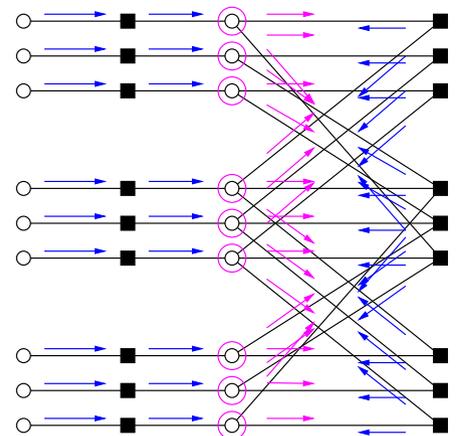
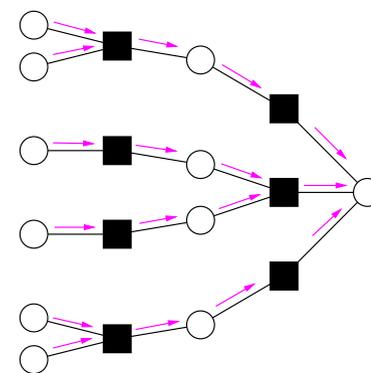
i -th iteration



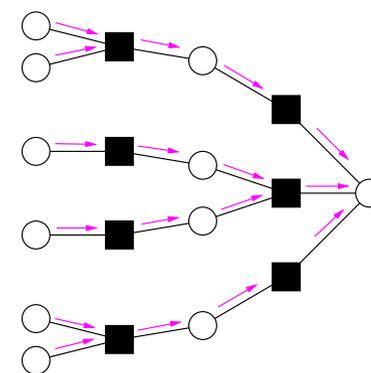
$i.5$ -th iteration



computation tree (without channel function nodes) ...
... where root is bit node 2

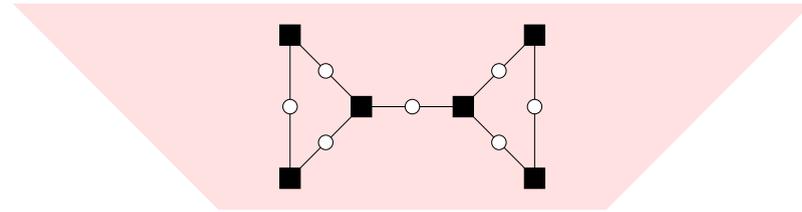


... where root is a copy of bit node 2

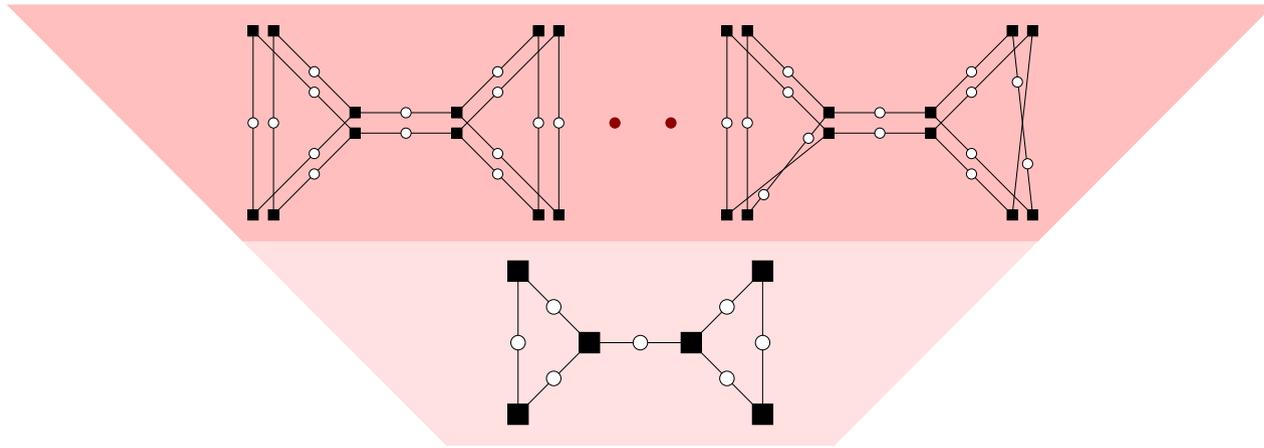


Graph Cover Hierarchy

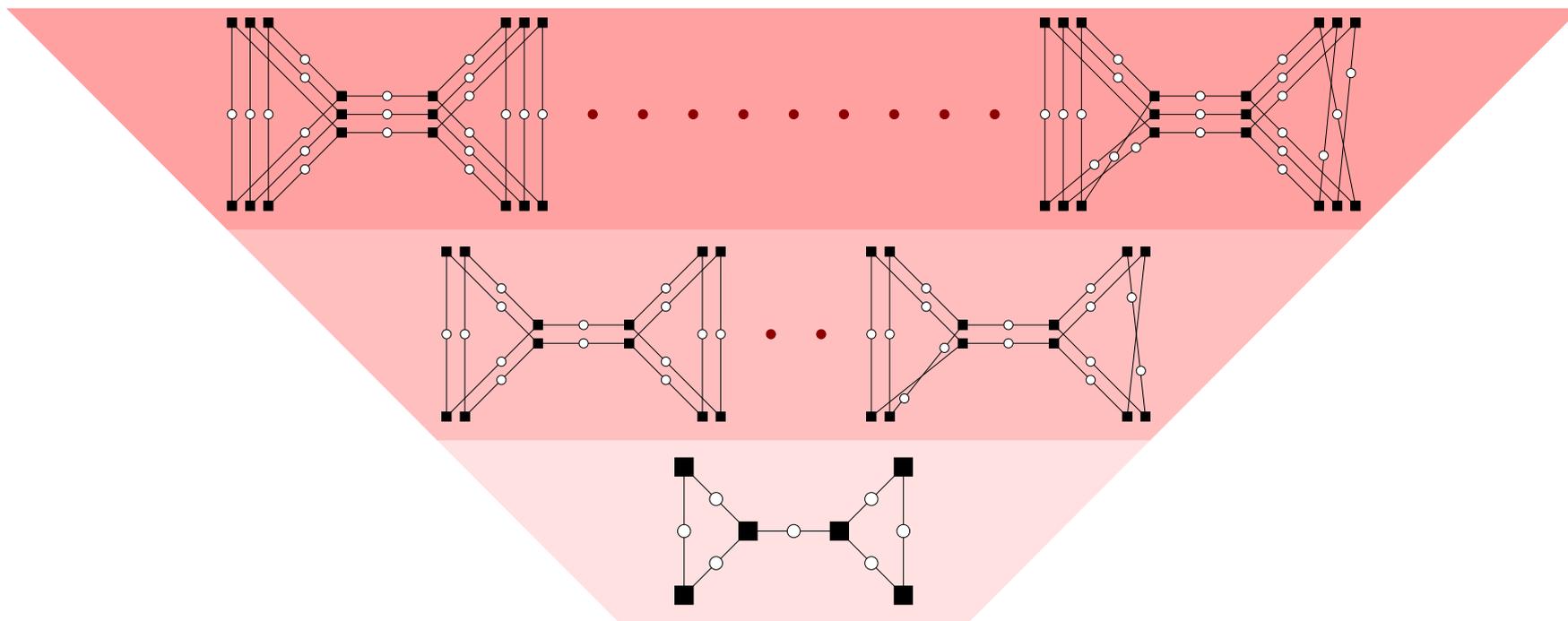
Graph Cover Hierarchy



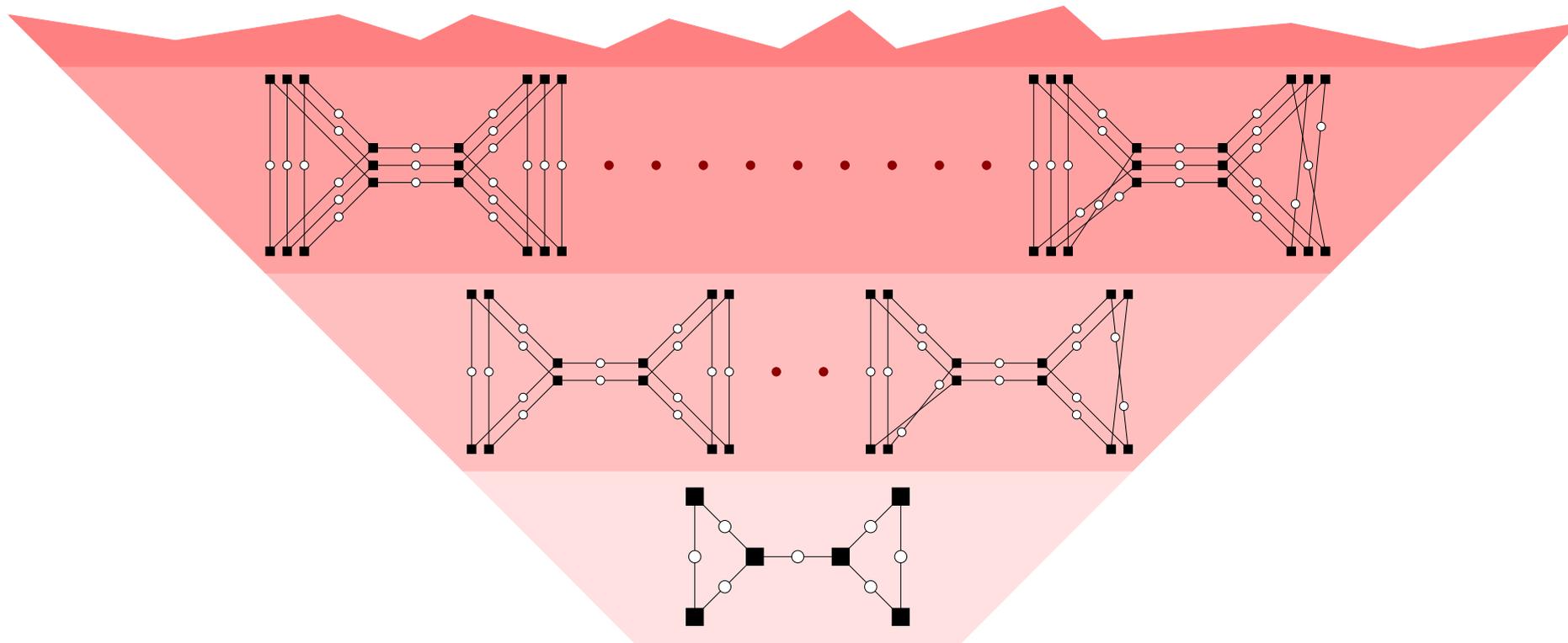
Graph Cover Hierarchy

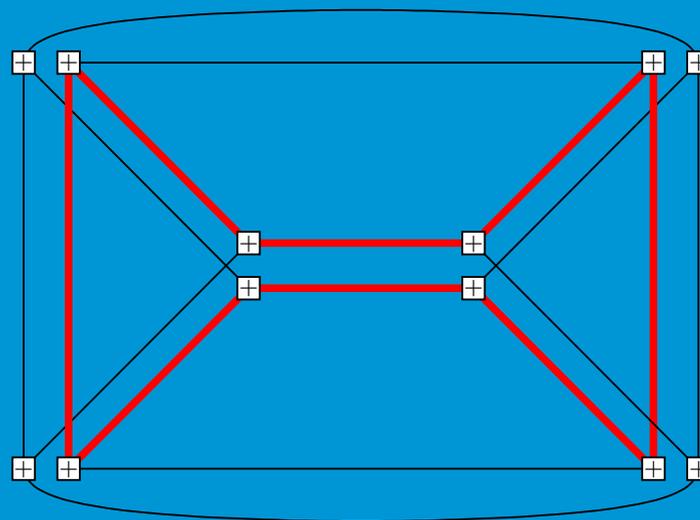
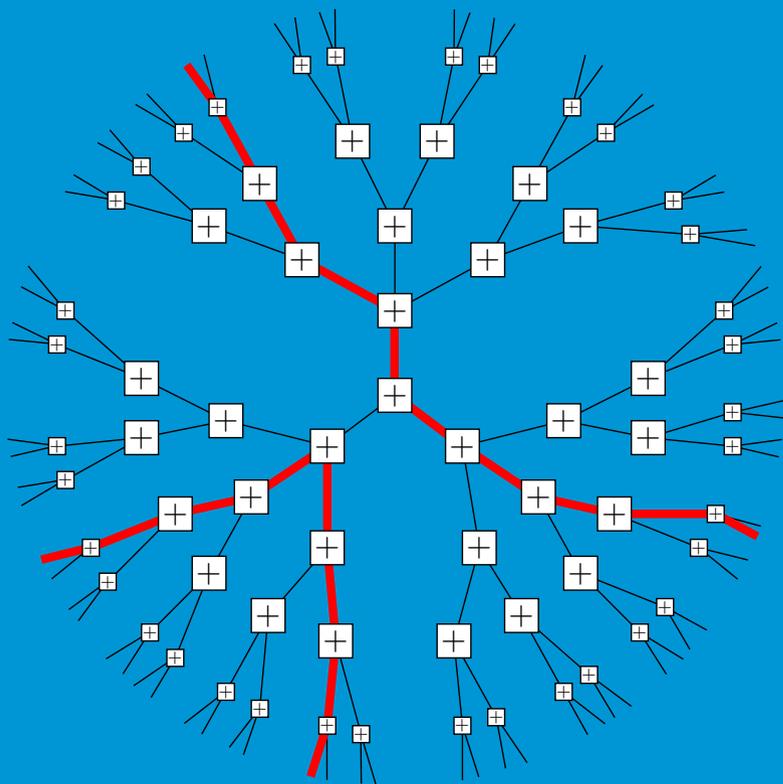
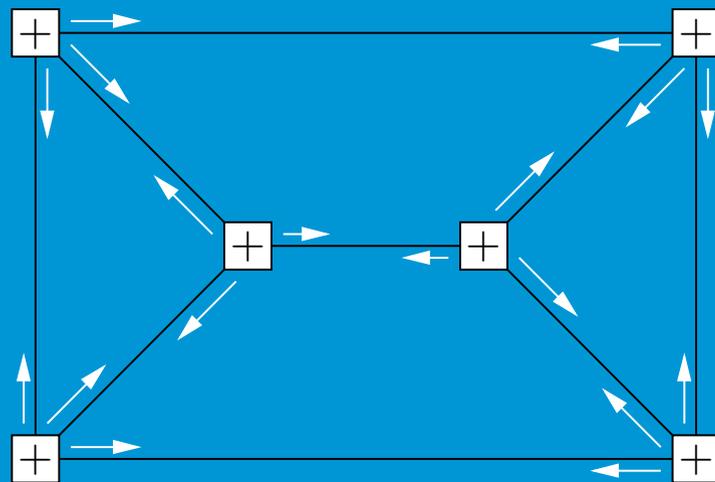


Graph Cover Hierarchy



Graph Cover Hierarchy





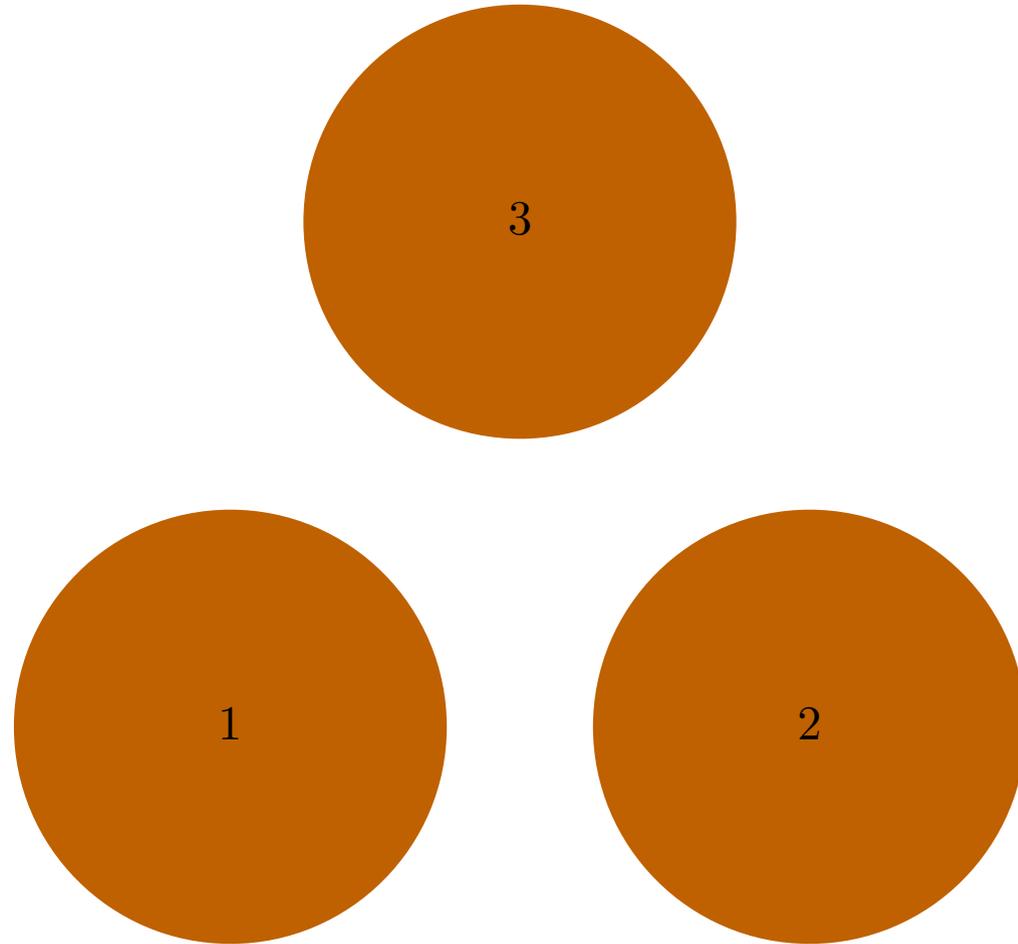
$$\zeta(V_1, \dots, V_n) = \sum_{\mathbf{k}} \zeta_{\mathbf{k}} \mathbf{V}^{\mathbf{k}} = \prod_{[\Gamma]} \frac{1}{1 - g(\Gamma, \mathbf{V})}$$

Pinball

Pinball

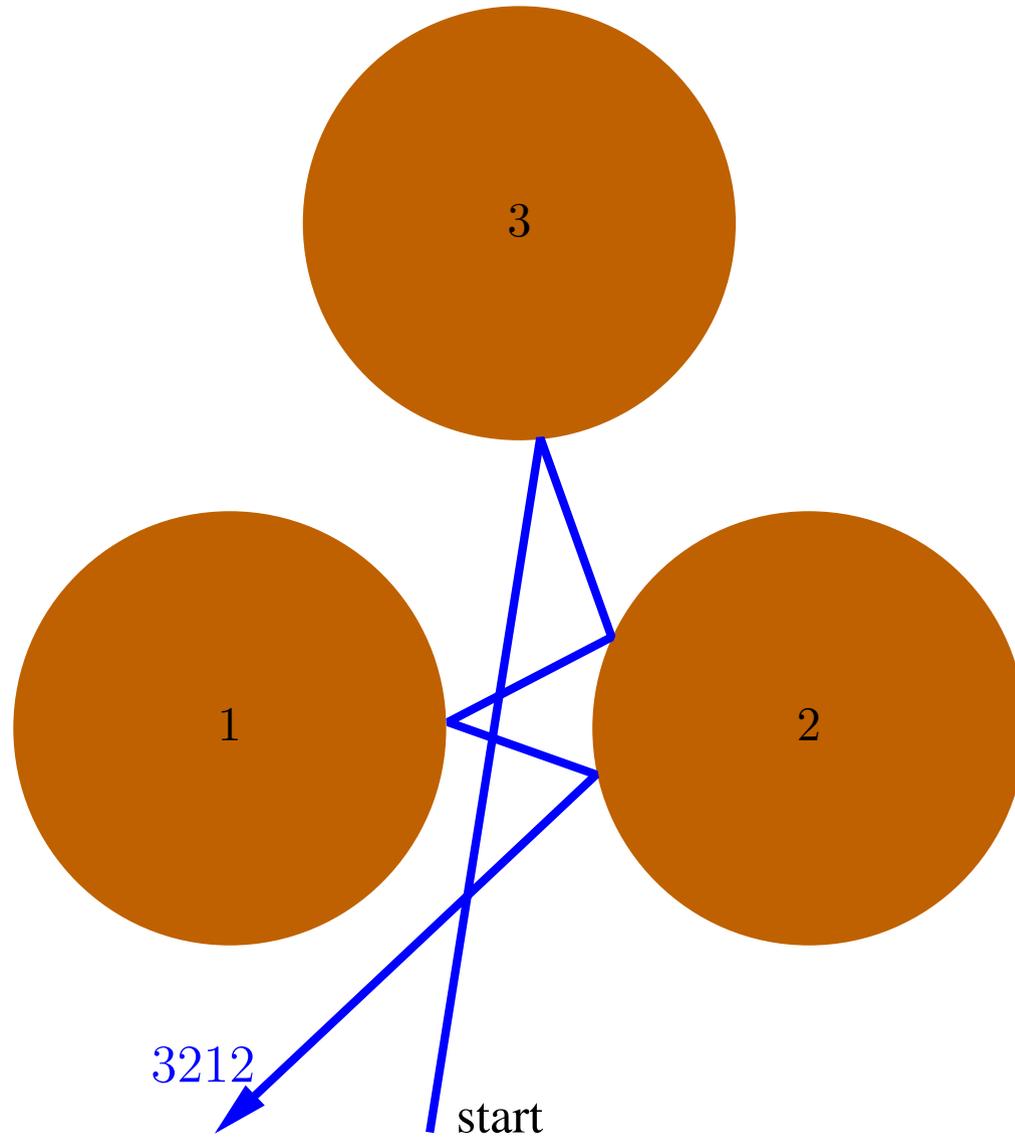


Pinball



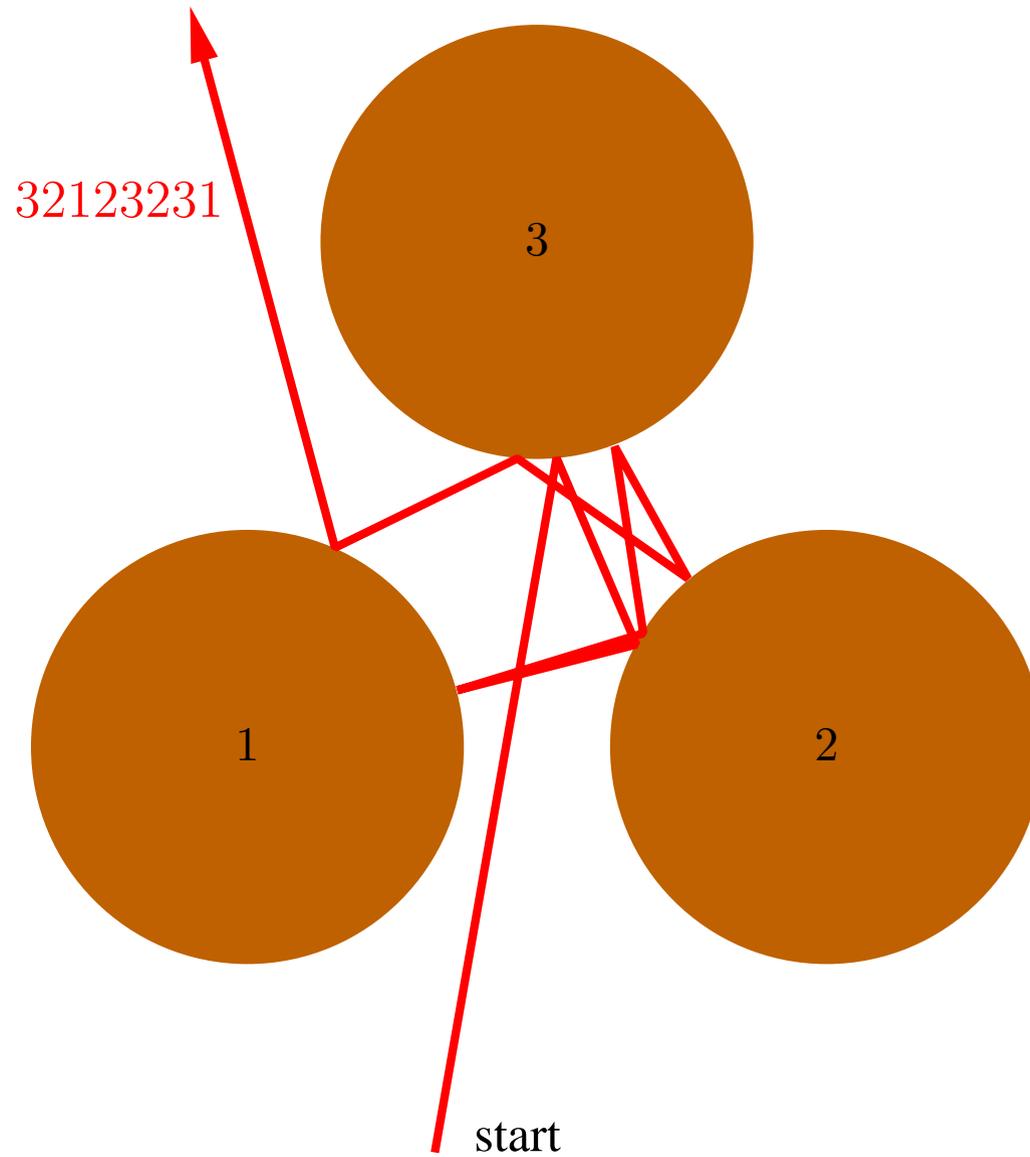
[picture adapted from chaosbook.org]

Pinball



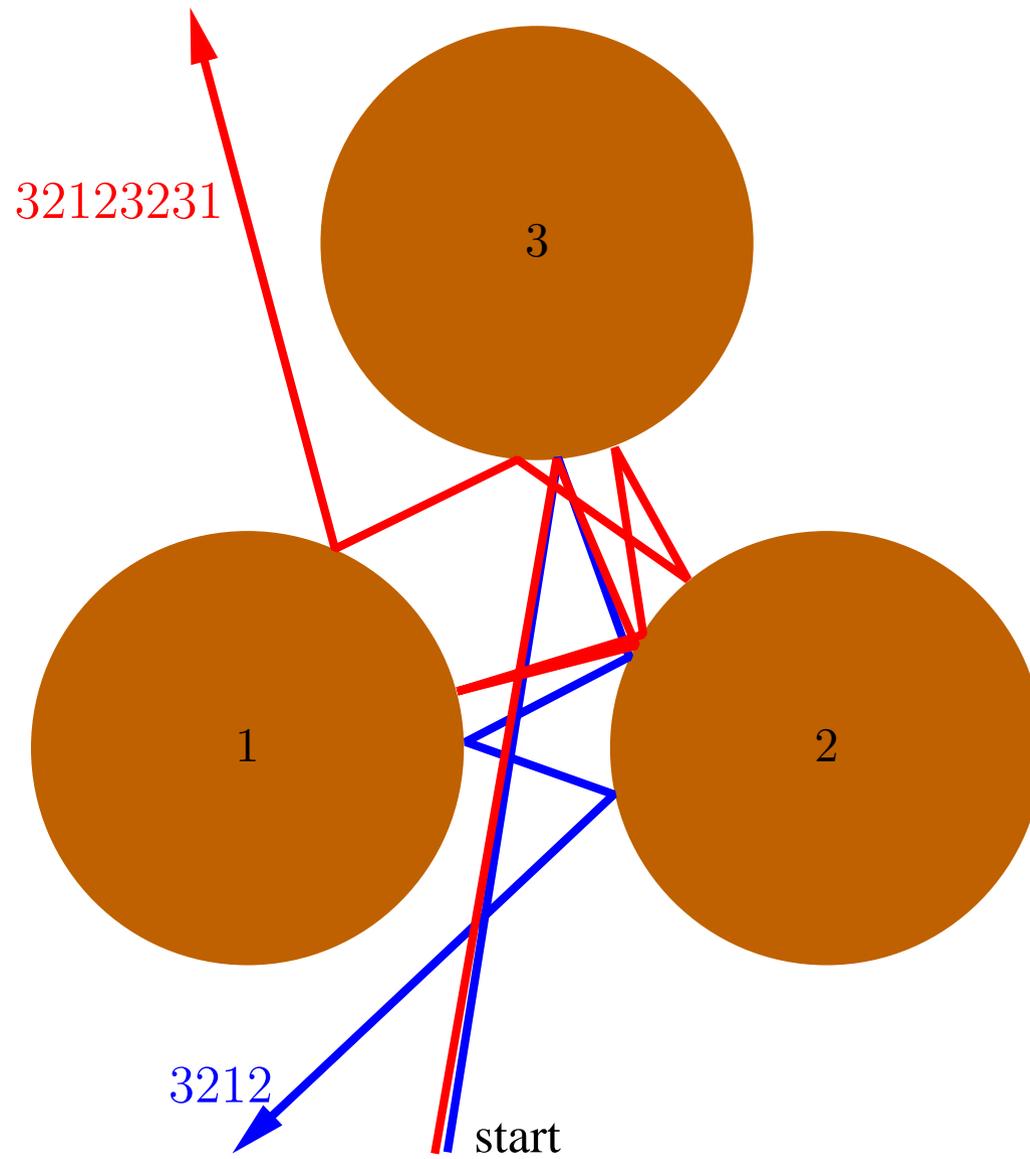
[picture adapted from chaosbook.org]

Pinball



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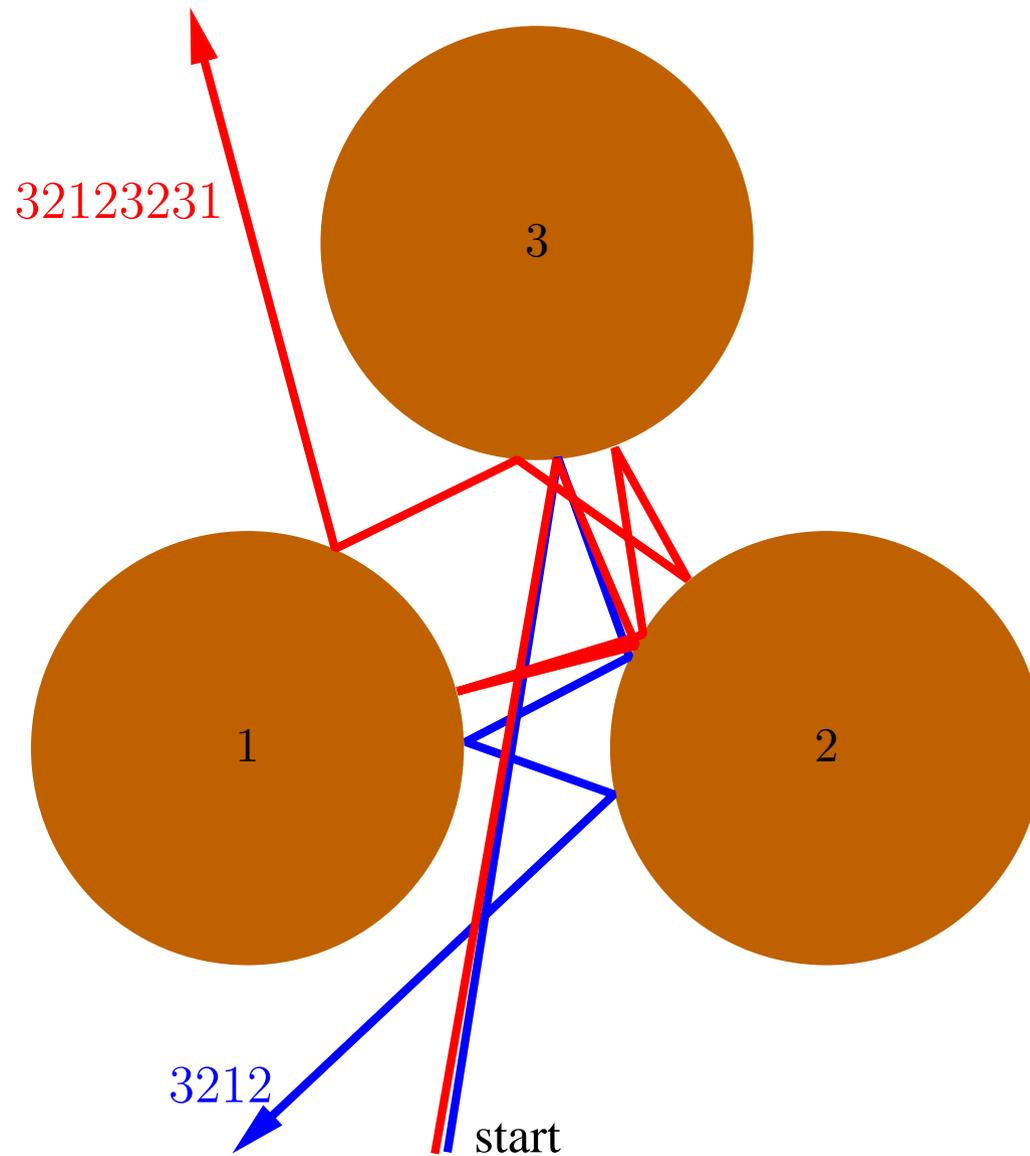
Pinball



[picture adapted from chaosbook.org]

Pinball

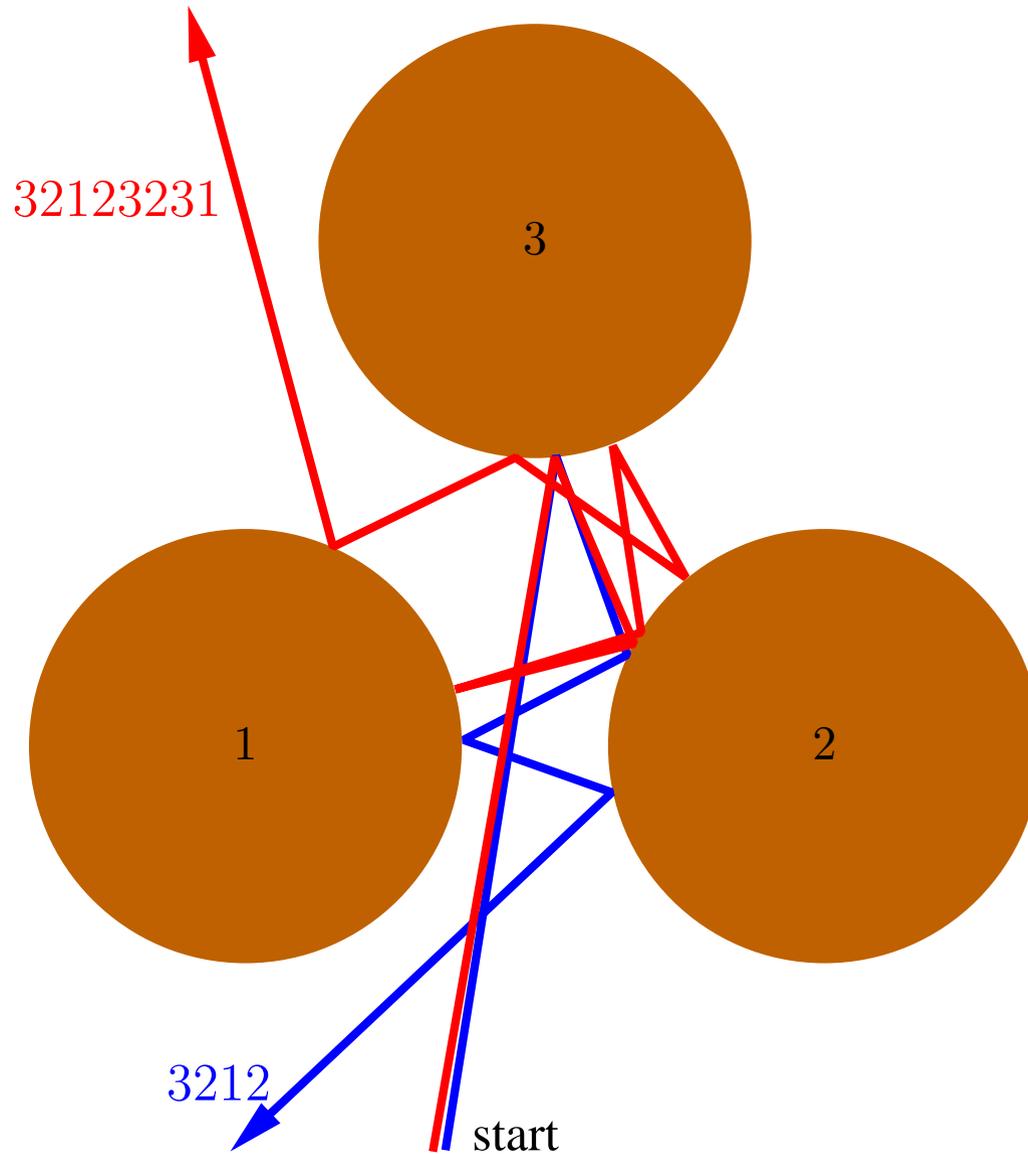
The trajectories are difficult to predict.



[picture adapted from chaosbook.org]

Pinball

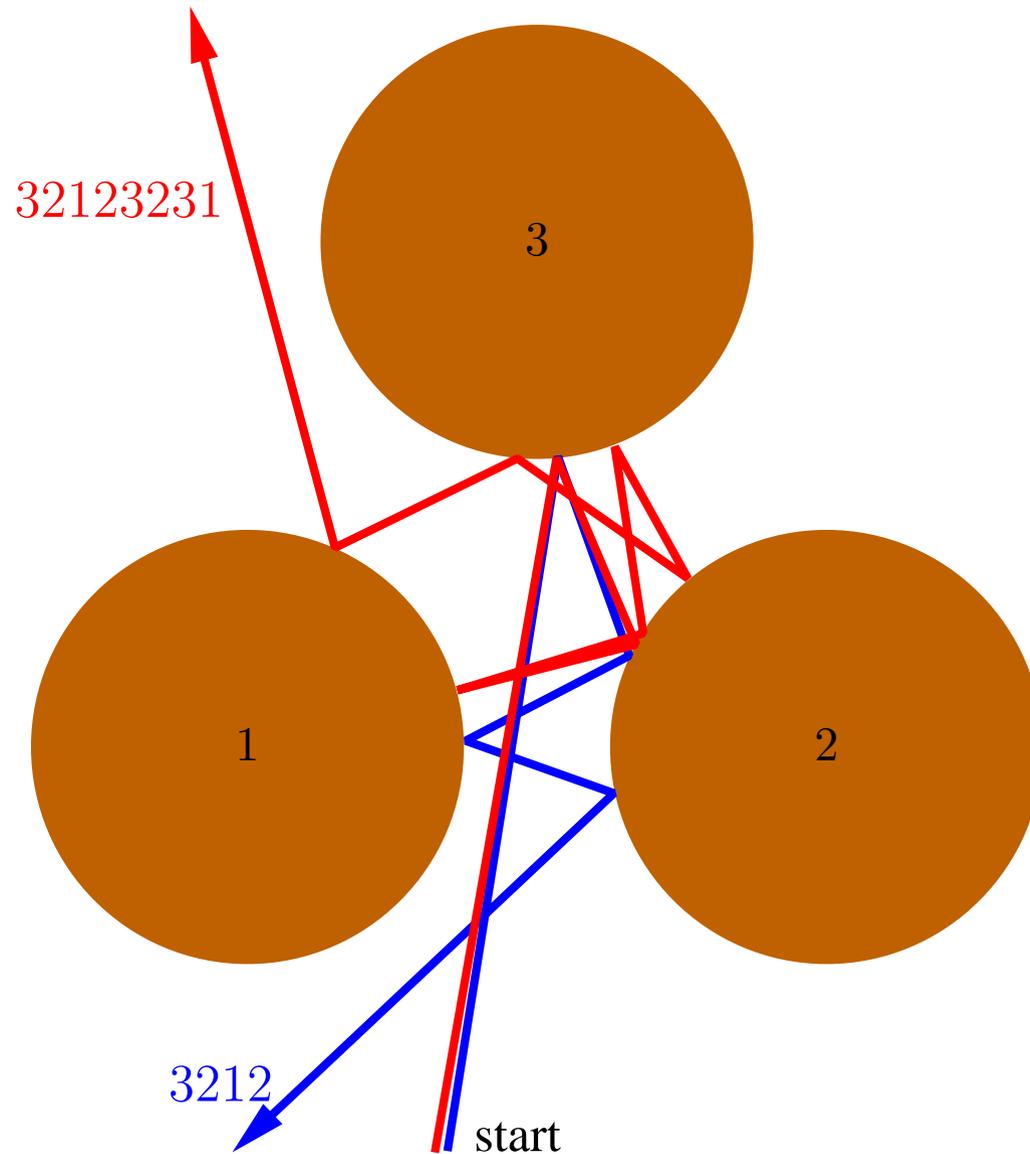
The trajectories are difficult to predict.
“chaotic system”



[picture adapted from chaosbook.org]

Pinball

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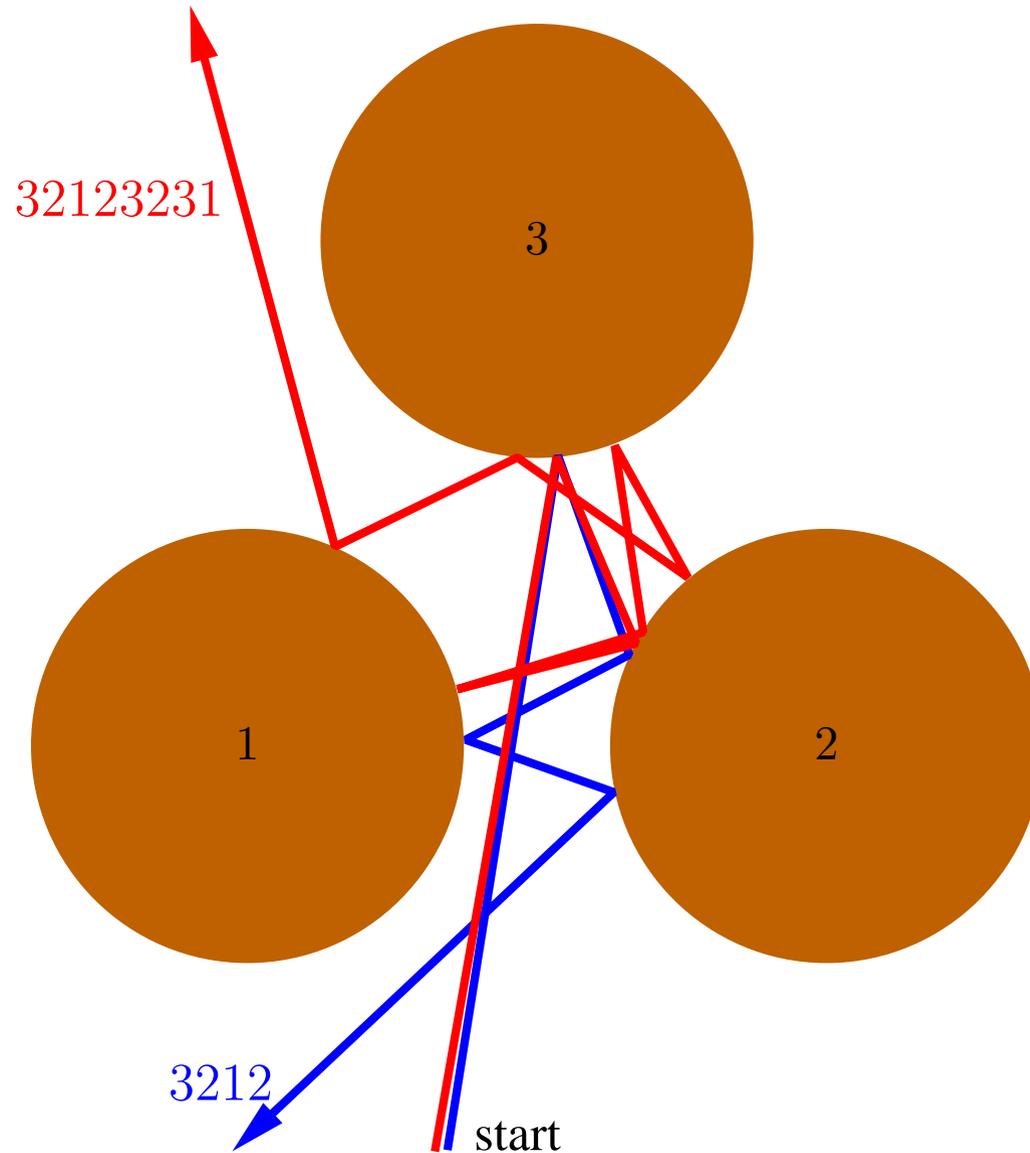


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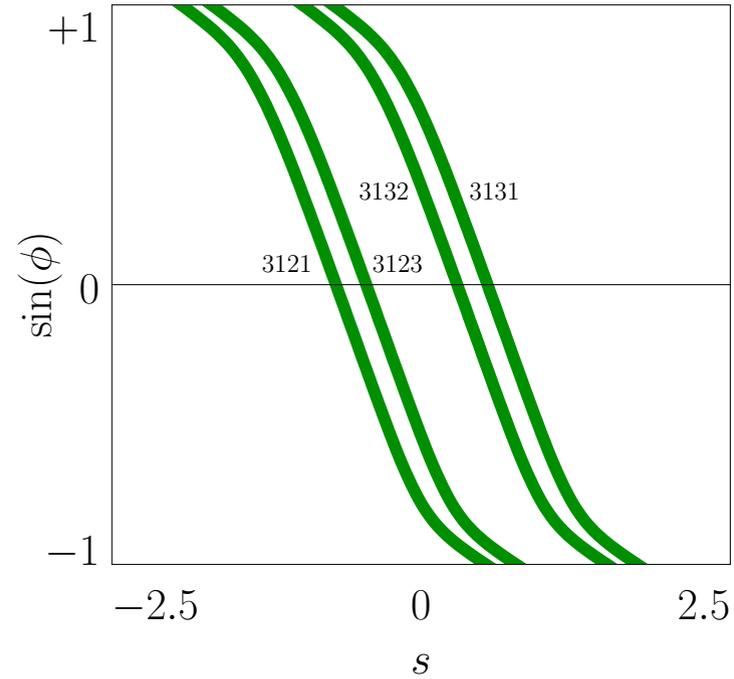
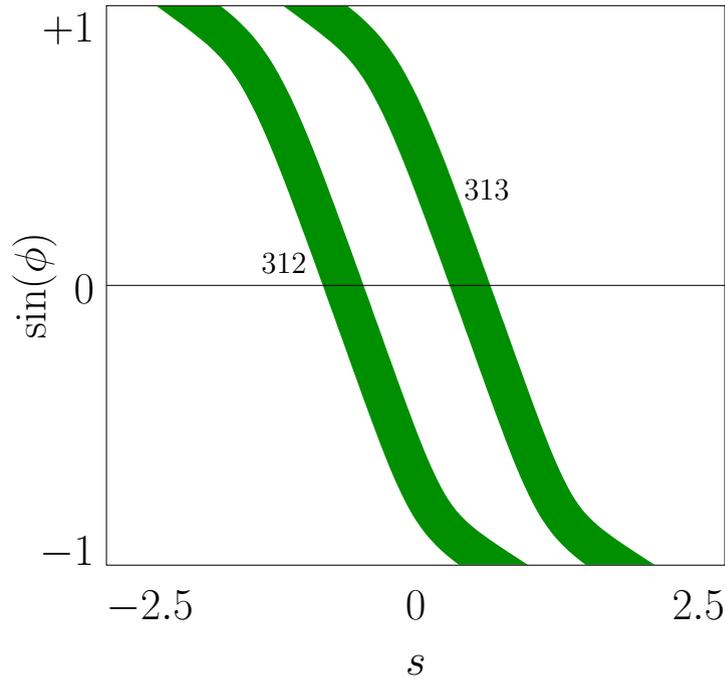
Pinball

The trajectory is difficult to predict.

However, quantities like the escape rate can be quantified.

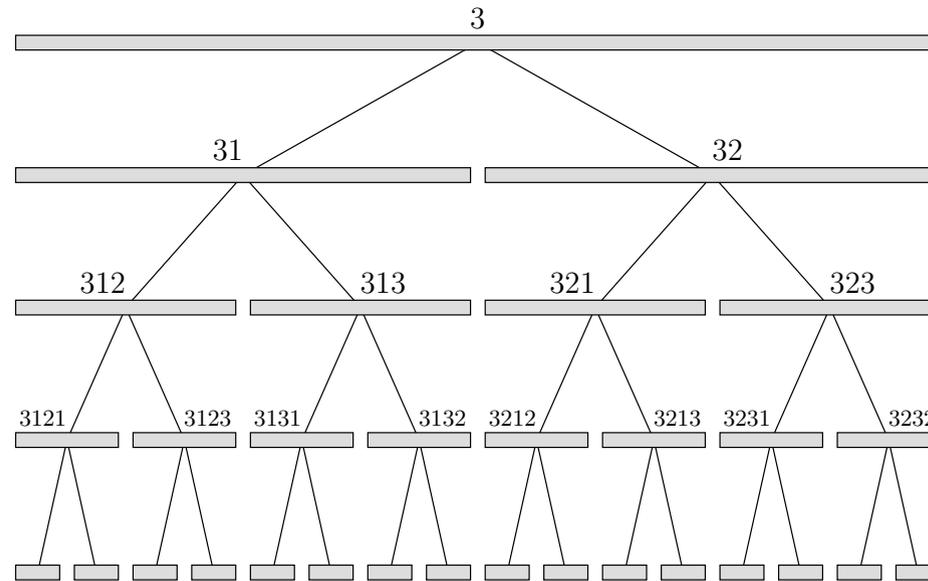


Pinball



- \mathcal{M}_3 : initial conditions for which the ball bounces at 3.
- \mathcal{M}_{31} : initial conditions for which the ball bounces at 3, 1.
- \mathcal{M}_{312} : initial conditions for which the ball bounces at 3, 1, 2.
- \mathcal{M}_{3121} : initial conditions for which the ball bounces at 3, 1, 2, 1.
- \dots : \dots

Pinball



[picture adapted from chaosbook.org]

Pinball

$$\hat{\theta}_1 = \frac{|\mathcal{M}_1|}{|\mathcal{M}|} + \frac{|\mathcal{M}_2|}{|\mathcal{M}|} + \frac{|\mathcal{M}_3|}{|\mathcal{M}|}$$

Pinball

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Pinball

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⋮

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Pinball

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γ : escape rate

Pinball

- Ideally, we compute $\hat{\theta}_1, \hat{\theta}_2, \hat{\theta}_3, \dots$, and determine from this γ .

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$$\hat{\theta}(z) = \sum_{n=1}^{\infty} \hat{\theta}_n z^n$$

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Pinball

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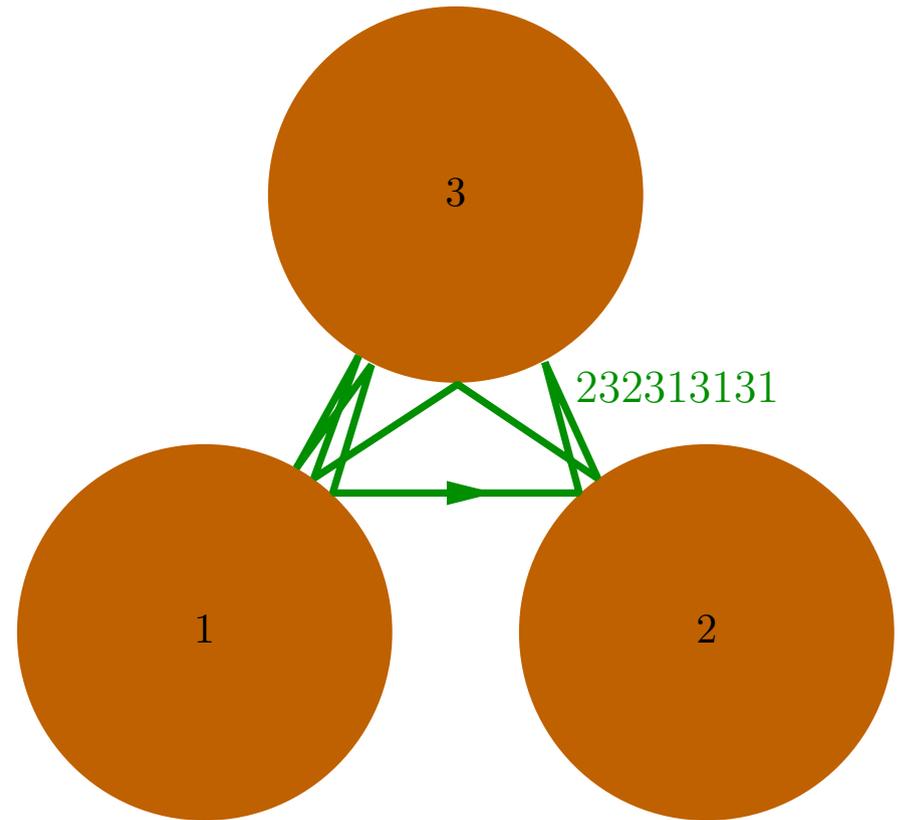
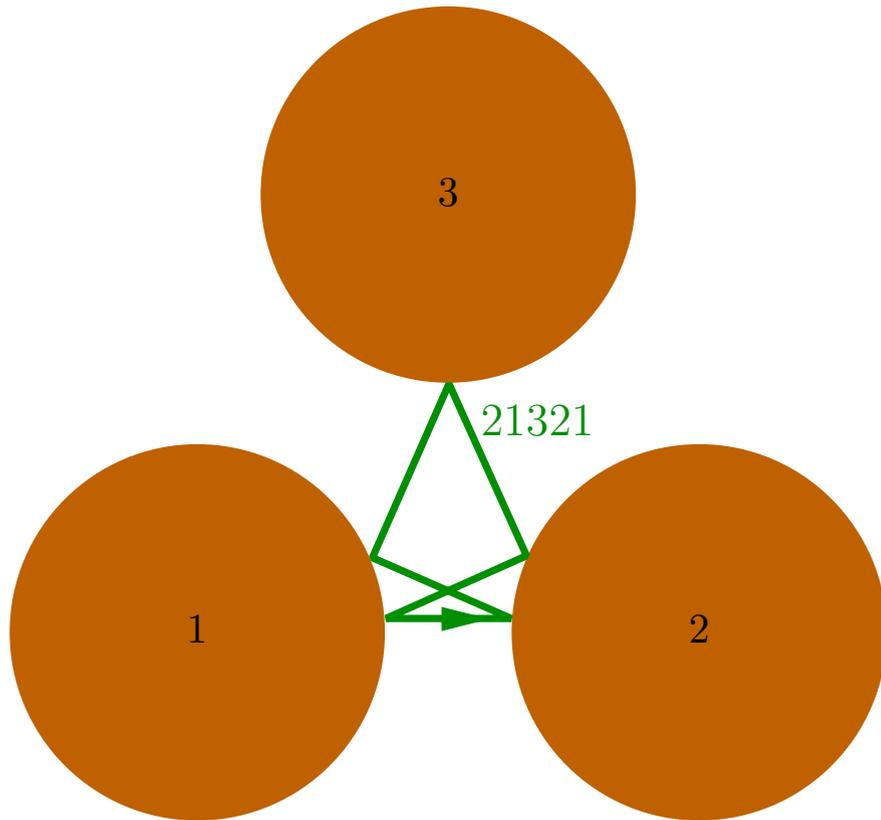
- Alternative approach: set up a **new power series**

$$\theta(z) = \sum_{n=1}^{\infty} \theta_n z^n$$

so that its **convergence radius** equals $\exp(\gamma)$.

Pinball

Main idea: look at periodic trajectories.



[picture adapted from chaosbook.org]

Pinball

Pinball

- Let the string **s** label the periodic trajectories.

Pinball

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- Let the periodic trajectory s go through x_s .

Pinball

- Let the string \mathbf{s} label the periodic trajectories.
- Let the periodic trajectory \mathbf{s} go through $x_{\mathbf{s}}$.
- Let the periodic trajectory \mathbf{s} have period $T_{\mathbf{p},\mathbf{s}}$.

Pinball

- Let the string \mathbf{s} label the periodic trajectories.
- Let the periodic trajectory \mathbf{s} go through $x_{\mathbf{s}}$.
- Let the periodic trajectory \mathbf{s} have period $T_{\mathbf{p},\mathbf{s}}$.
- Then define

$$\begin{aligned}\theta(z) &\triangleq \sum_{n=1}^{\infty} z^n \sum_{\text{sequence } \mathbf{s} \text{ of length } n} \frac{1}{|\Lambda_{\mathbf{s}}|} \\ &= \frac{z^1}{|\Lambda_1|} + \frac{z^1}{|\Lambda_2|} + \frac{z^1}{|\Lambda_3|} + \frac{z^2}{|\Lambda_{12}|} + \frac{z^2}{|\Lambda_{13}|} + \dots\end{aligned}$$

where $\Lambda_{\mathbf{s}}$ is the unstable eigenvalue of the **Jacobian matrix** $J^t(x_i)$ evaluated for $t = T_{\mathbf{p},\mathbf{s}}$. (Due to the low dimensionality, the Jacobian can have at most one unstable eigenvalue for the present setup.)

Pinball

- $\theta(z)$ can be rewritten as follows:

$$\theta(z) = \sum_{\text{prime cycle } \mathbf{p}} n_{\mathbf{p}} \sum_{r=1}^{\infty} \left(\frac{z^{n_{\mathbf{p}}}}{|\Lambda_{\mathbf{p}}|} \right)^r$$

Pinball

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Pinball

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- Definition of **dynamical zeta function**:

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Pinball

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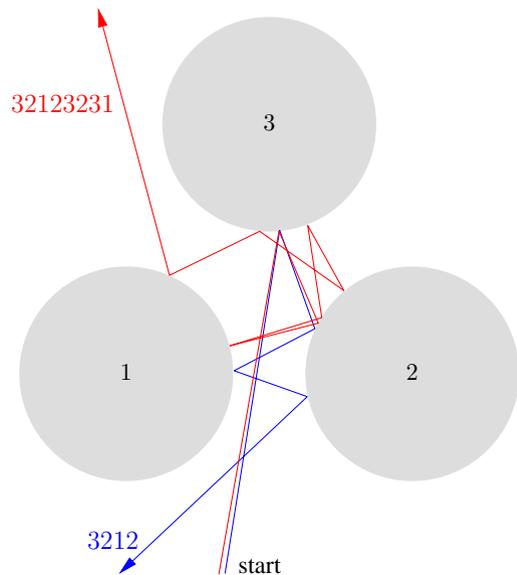
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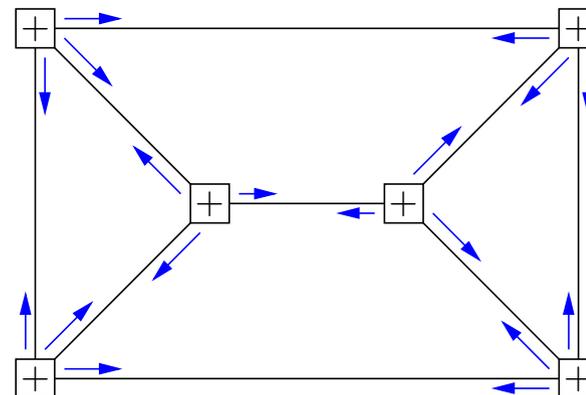
-
- Note:

$$\theta(z) = z \frac{d}{dz} \log(\zeta(z))$$

Analogy Pinball vs. MPI Decoding



pinball



message-passing iterative decoding
of cycle codes

trajectory

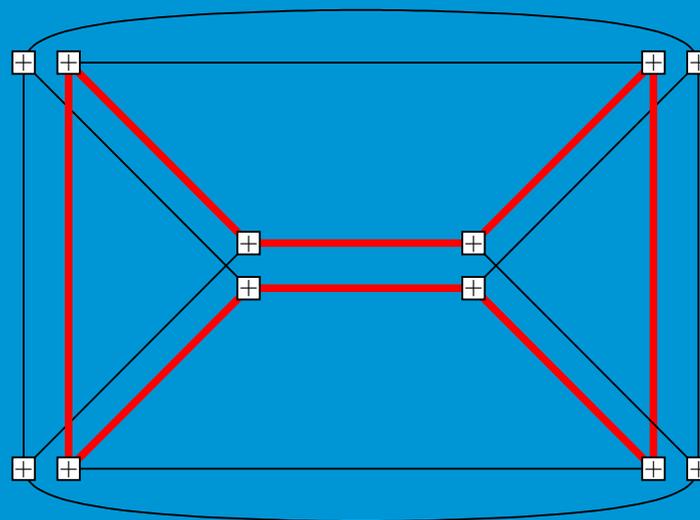
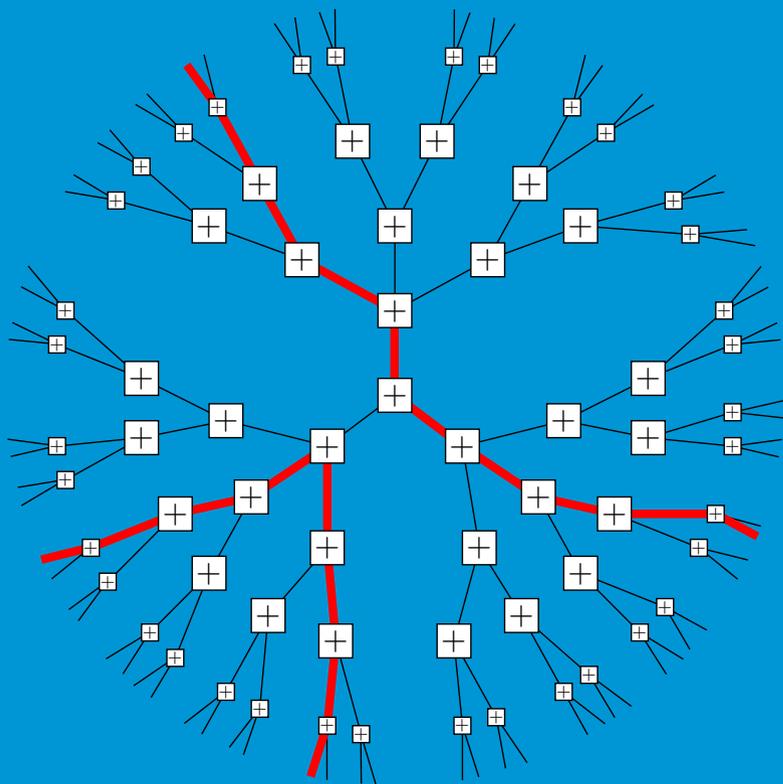
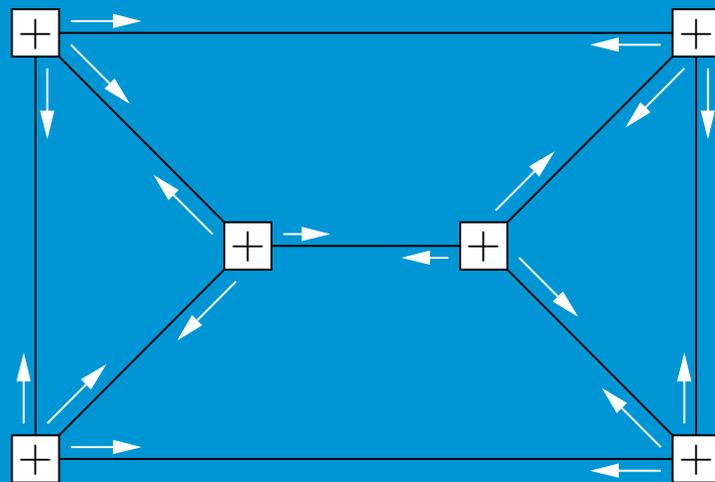
minimal deviation in computation trees

periodic trajectory

codeword in finite graph cover /
graph-cover pseudo-codeword

dynamical edge zeta function

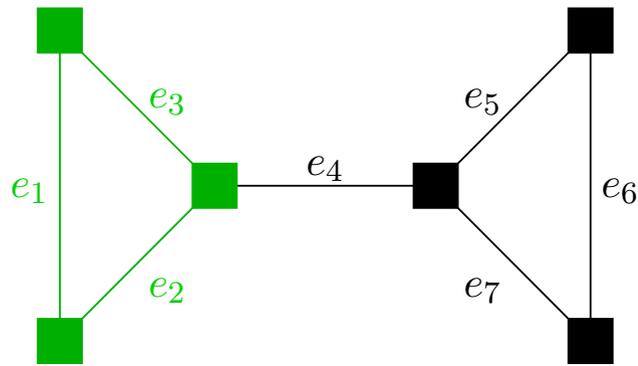
graph zeta function



$$\zeta(V_1, \dots, V_n) = \sum_{\mathbf{k}} \zeta_{\mathbf{k}} \mathbf{V}^{\mathbf{k}} = \prod_{[\Gamma]} \frac{1}{1 - g(\Gamma, \mathbf{V})}$$

The Edge Zeta Function of a Graph

Definition (Hashimoto, see also Stark/Terras):



Here: $\Gamma = (e_1, e_2, e_3)$

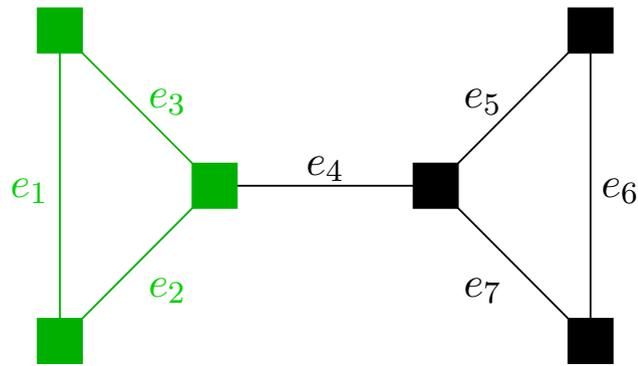
Let Γ be a path in a graph X with edge-set E ; write

$$\Gamma = (e_{i_1}, \dots, e_{i_k})$$

to indicate that Γ begins with the edge e_{i_1} and ends with the edge e_{i_k} .

The Edge Zeta Function of a Graph

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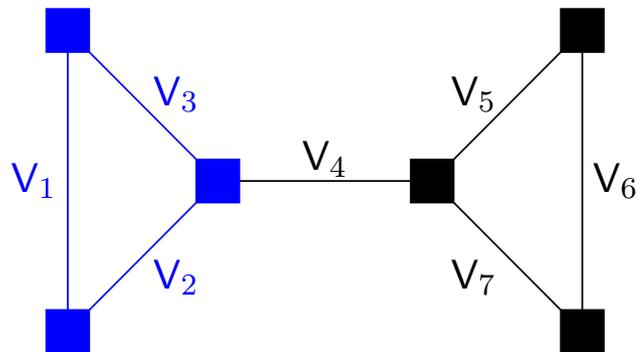


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to indicate that Γ begins with the edge e_{i_1} and ends with the edge e_{i_k} .



Here: $g(\Gamma, \mathbf{V}) = V_1 V_2 V_3$

The **monomial of Γ** is given by

$$g(\Gamma, \mathbf{V}) \triangleq V_{i_1} \cdots V_{i_k},$$

where the V_i 's are indeterminates.

The Edge Zeta Function of a Graph

Definition (Hashimoto, see also Stark/Terras):

The **edge zeta function of X** is defined to be the **power series**

$$\zeta_X(\mathbf{V}) = \zeta_X(V_1, \dots, V_n) \in \mathbb{Z}[[V_1, \dots, V_n]]$$

given by

$$\zeta_X(\mathbf{V}) = \zeta_X(V_1, \dots, V_n) = \prod_{[\Gamma] \in A(X)} \frac{1}{1 - g(\Gamma, \mathbf{V})},$$

where $A(X)$ is the collection of equivalence classes of

backtrackless, tailless, primitive cycles in X .

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where $A(X)$ is the collection of equivalence classes of

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Note: unless X contains only one cycle,
the set $A(X)$ will be countably infinite.

The Edge Zeta Function of a Graph

Theorem (Bass):

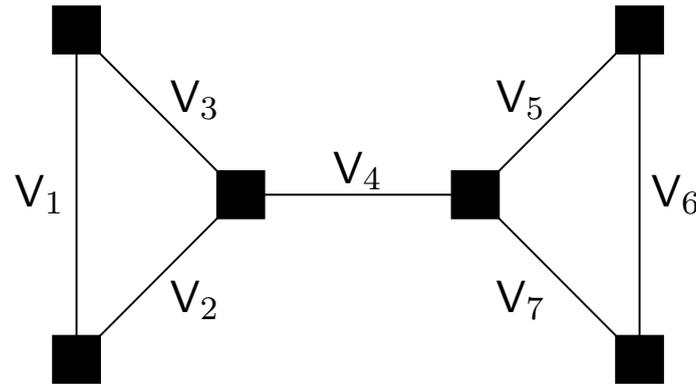
- The edge zeta function $\zeta_X(V_1, \dots, V_n)$ is a **rational function**.
- More precisely, for any directed graph \vec{X} of X , we have

$$\zeta_X(V_1, \dots, V_n) = \frac{1}{\det(\mathbf{I} - \mathbf{V}\mathbf{M}(\vec{X}))} = \frac{1}{\det(\mathbf{I} - \mathbf{M}(\vec{X})\mathbf{V})}$$

where

- \mathbf{I} is the identity matrix of size $2n$,
- $\mathbf{V} = \text{diag}(V_1, \dots, V_n, V_1, \dots, V_n)$ is a diagonal matrix of indeterminants.
- $\mathbf{M}(\vec{X})$ is a $2n \times 2n$ matrix derived from some directed graph version \vec{X} of X .

Example of Edge Zeta Function



This normal graph N has the following edge zeta function:

$$\zeta_N(V_1, \dots, V_7) = \frac{1}{\det(\mathbf{I}_{14} - \mathbf{VM})}$$

$$= \frac{1}{1 - 2V_1V_2V_3 + V_1^2V_2^2V_3^2 - 2V_5V_6V_7 + 4V_1V_2V_3V_5V_6V_7 - 2V_1^2V_2^2V_3^2V_5V_6V_7 - 4V_1V_2V_3V_4^2V_5V_6V_7 + 4V_1^2V_2^2V_3^2V_4^2V_5V_6V_7 + V_5^2V_6^2V_7^2 - 2V_1V_2V_3V_5^2V_6^2V_7^2 + V_1^2V_2^2V_3^2V_5^2V_6^2V_7^2 + 4V_1V_2V_3V_4^2V_5^2V_6^2V_7^2 - 4V_1^2V_2^2V_3^2V_4^2V_5^2V_6^2V_7^2}$$

Example of Edge Zeta Function

The Taylor series expansion is

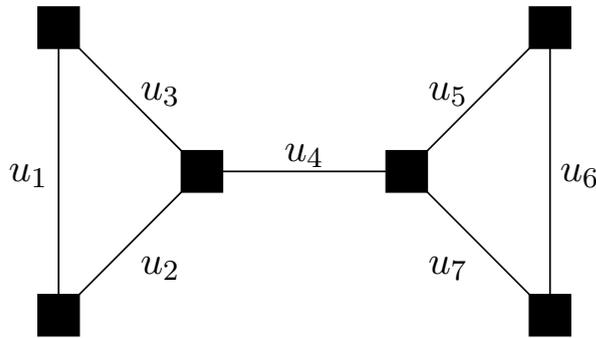
$$\zeta_N(V_1, \dots, V_7)$$

$$= 1 + 2V_1V_2V_3 + 3V_1^2V_2^2V_3^2 + 2V_5V_6V_7$$

$$+ 4V_1V_2V_3V_5V_6V_7 + 6V_1^2V_2^2V_3^2V_5V_6V_7$$

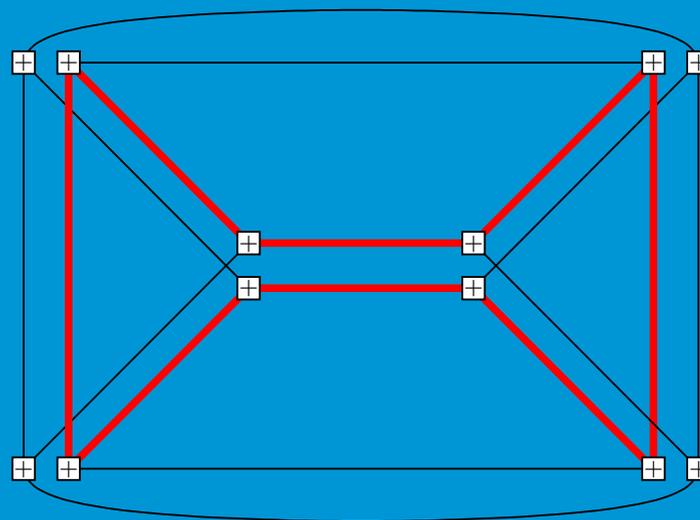
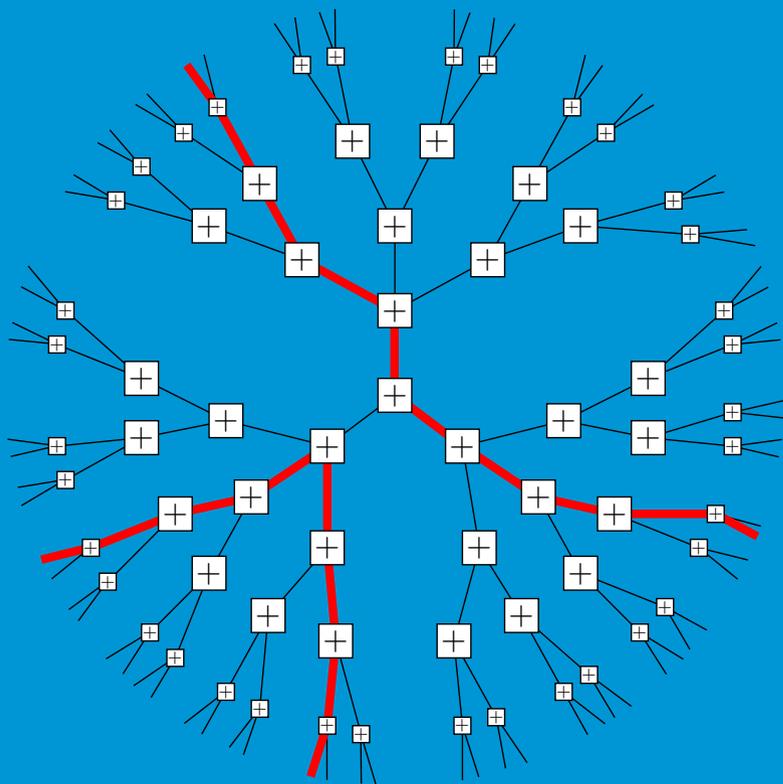
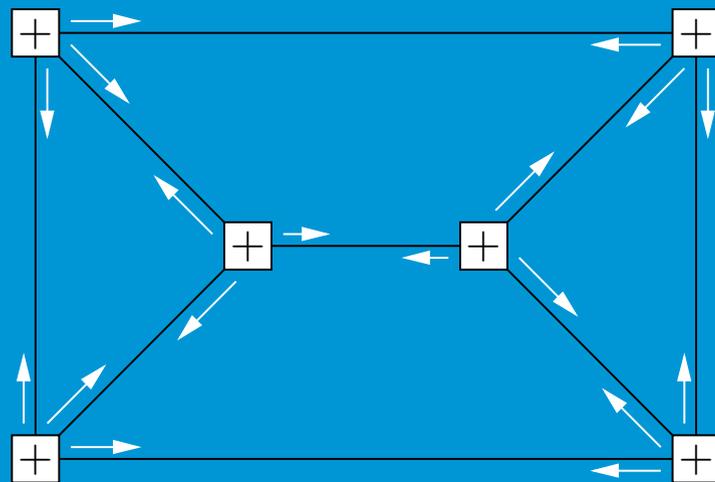
$$+ 4V_1V_2V_3V_4^2V_5V_6V_7 + 12V_1^2V_2^2V_3^2V_4^2V_5V_6V_7$$

$$+ \dots$$



We get the following exponent vectors:

(0, 0, 0, 0, 0, 0, 0)	codeword
(1, 1, 1, 0, 0, 0, 0)	codeword
(2, 2, 2, 0, 0, 0, 0)	pseudo-codeword (in \mathbb{Z} -span)
(0, 0, 0, 0, 1, 1, 1)	codeword
(1, 1, 1, 0, 1, 1, 1)	codeword
(2, 2, 2, 0, 1, 1, 1)	pseudo-codeword (in \mathbb{Z} -span)
(1, 1, 1, 2, 1, 1, 1)	pseudo-codeword (not in \mathbb{Z} -span)
(2, 2, 2, 2, 1, 1, 1)	pseudo-codeword (in \mathbb{Z} -span)



$$\zeta(V_1, \dots, V_n) = \sum_{\mathbf{k}} \zeta_{\mathbf{k}} \mathbf{V}^{\mathbf{k}} = \prod_{[\Gamma]} \frac{1}{1 - g(\Gamma, \mathbf{V})}$$

New Theorem for Cycle Codes

Rough statement:

$$\left(\begin{array}{l} \text{region of convergence} \\ \text{of } \text{sum-product algorithm} \\ \text{to the all-zero codeword} \end{array} \right) = \left(\begin{array}{l} \text{region of convergence} \\ \text{of the } \text{edge zeta function} \end{array} \right)$$

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More precisely:

$$\left(\begin{array}{l} \text{The **sum-product algorithm**} \\ \text{converges to the all-zero codeword} \\ \text{for the log-likelihood vector } \lambda \end{array} \right) \Leftrightarrow \left(\begin{array}{l} \mathbf{V} \text{ is in the region of convergence} \\ \text{of the **edge zeta function**,} \\ \text{where } V_e = \exp(-\lambda_e) \quad \forall e \end{array} \right)$$

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Note: global convergence result!

New Theorem for Cycle Codes

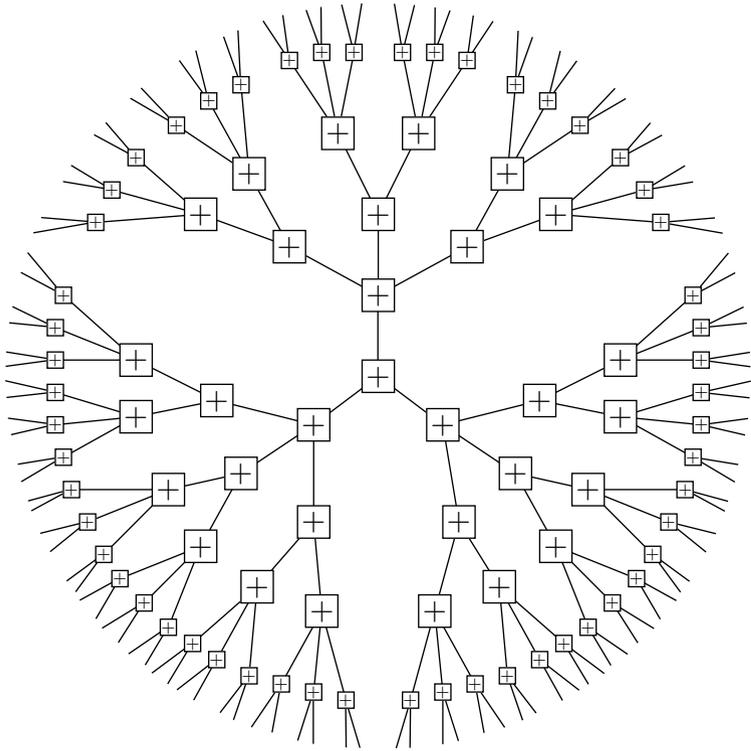
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Corollary:

The region of all log-likelihood vectors λ
for which the **sum-product algorithm** converges
to the all-zero codeword
is given by a **determinantal expression**.

Some intuition behind this statement



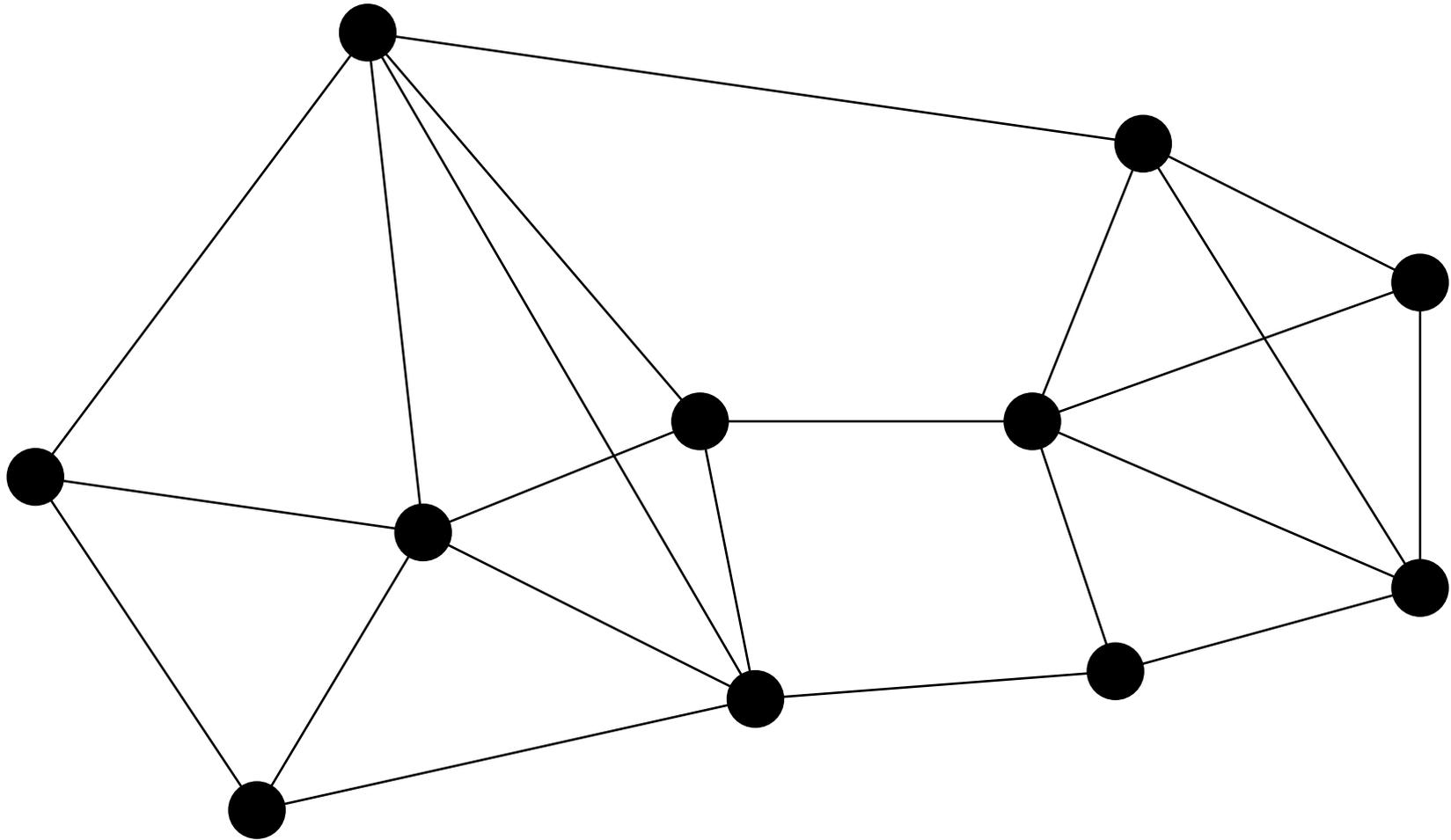
$$\begin{aligned}\zeta_N(\mathbf{V}_1, \dots, \mathbf{V}_n) &\triangleq \prod_{[\Gamma] \in A(N)} \frac{1}{1 - g(\Gamma, \mathbf{V})} \\ &= \frac{1}{\det(\mathbf{I} - \mathbf{M}(\vec{N})\mathbf{V})}\end{aligned}$$

It turns out that **key objects** for analyzing computation trees of the normal factor graph N are

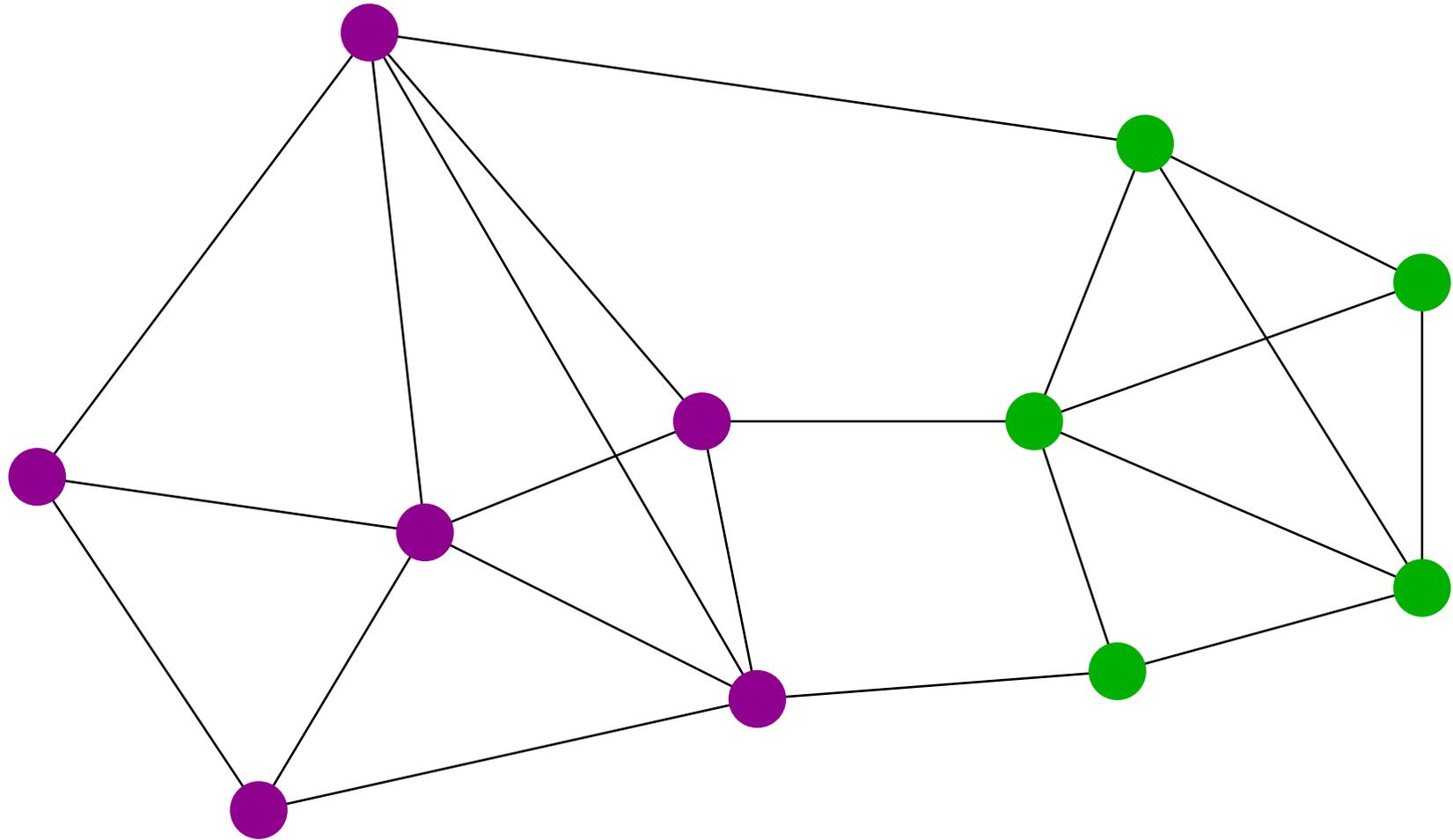
$$(\mathbf{M}(\vec{N})\mathbf{V})^k, \quad k \geq 0.$$

Community detection in networks

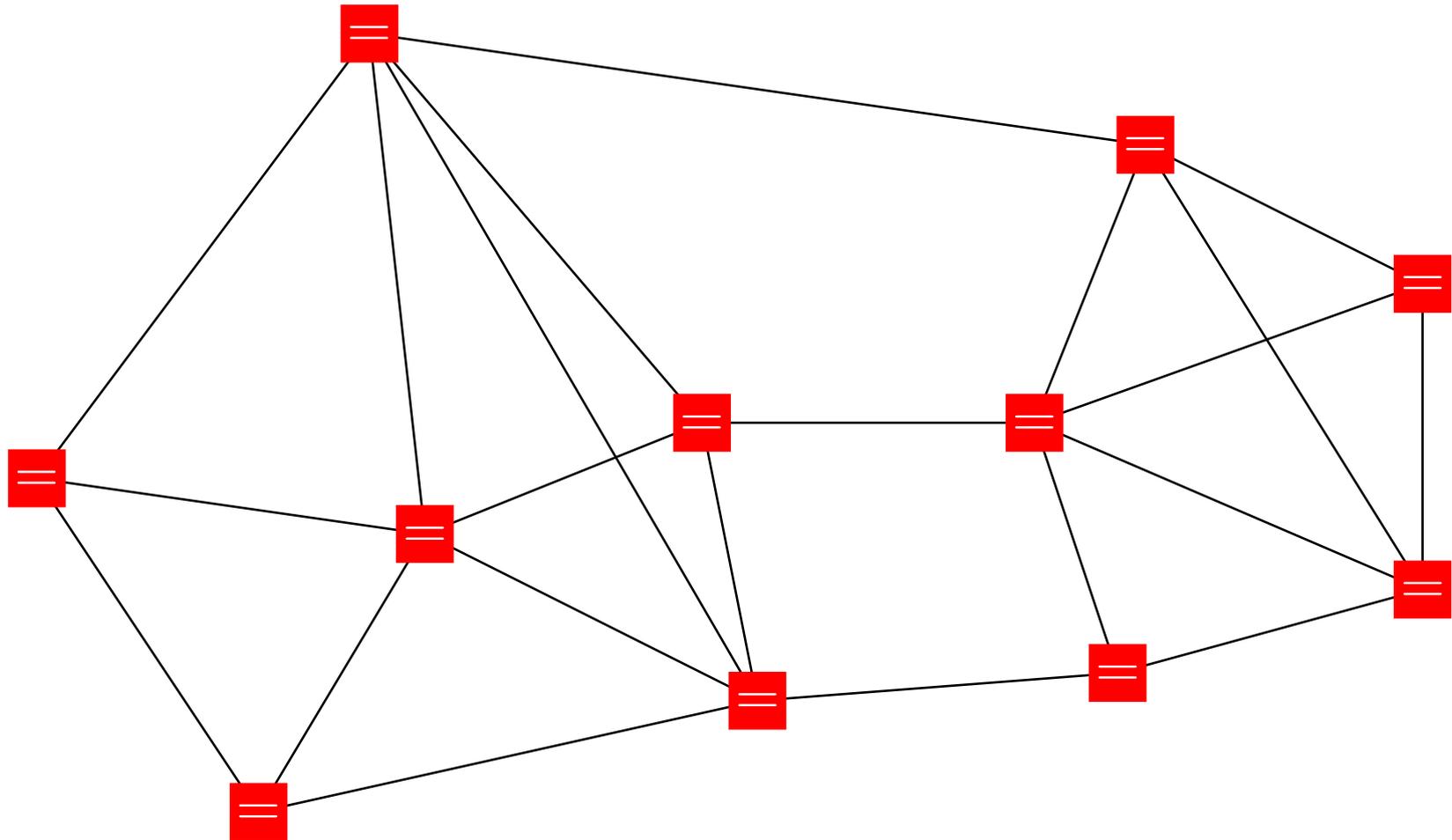
Community Detection in Networks



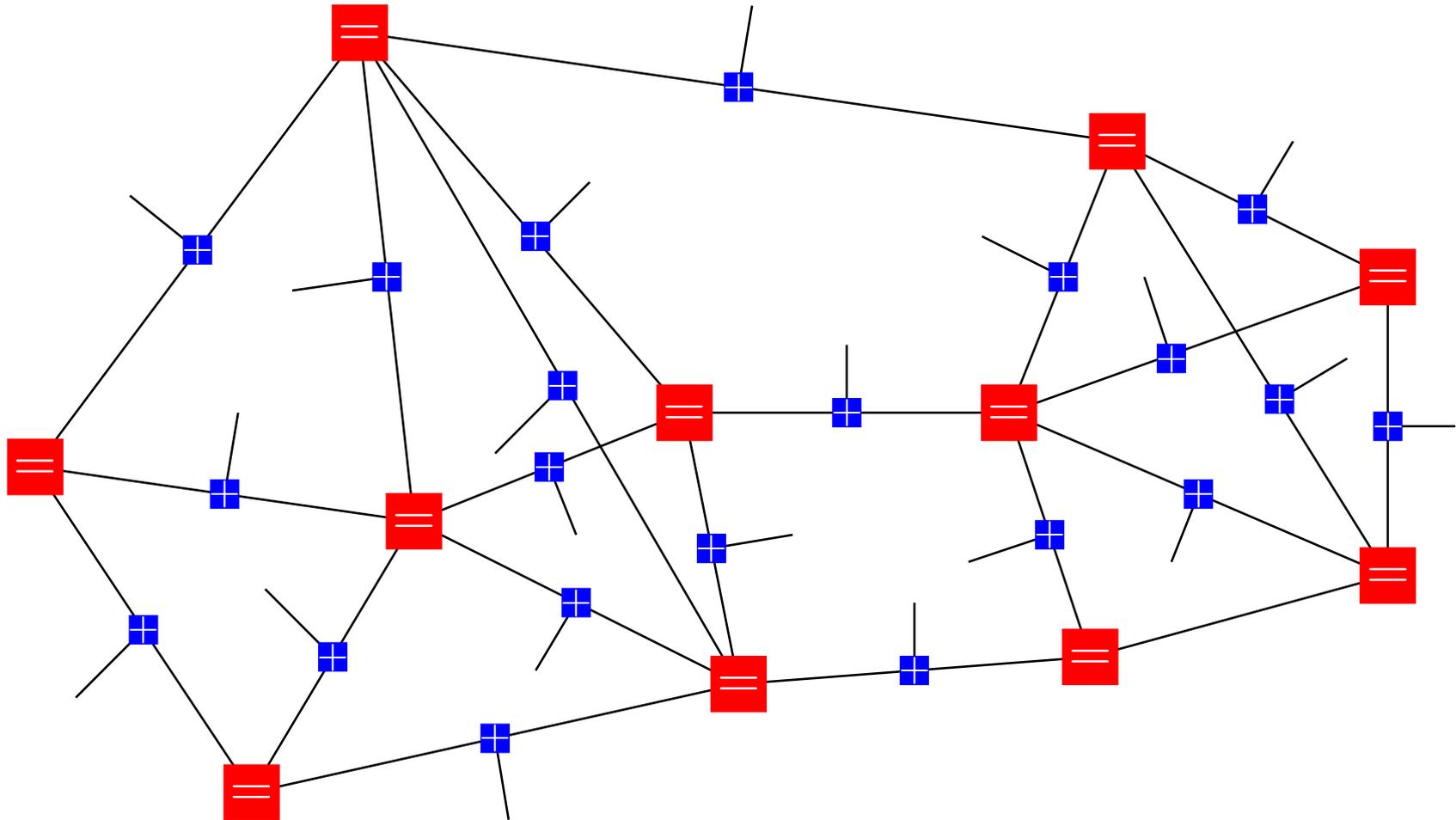
Community Detection in Networks



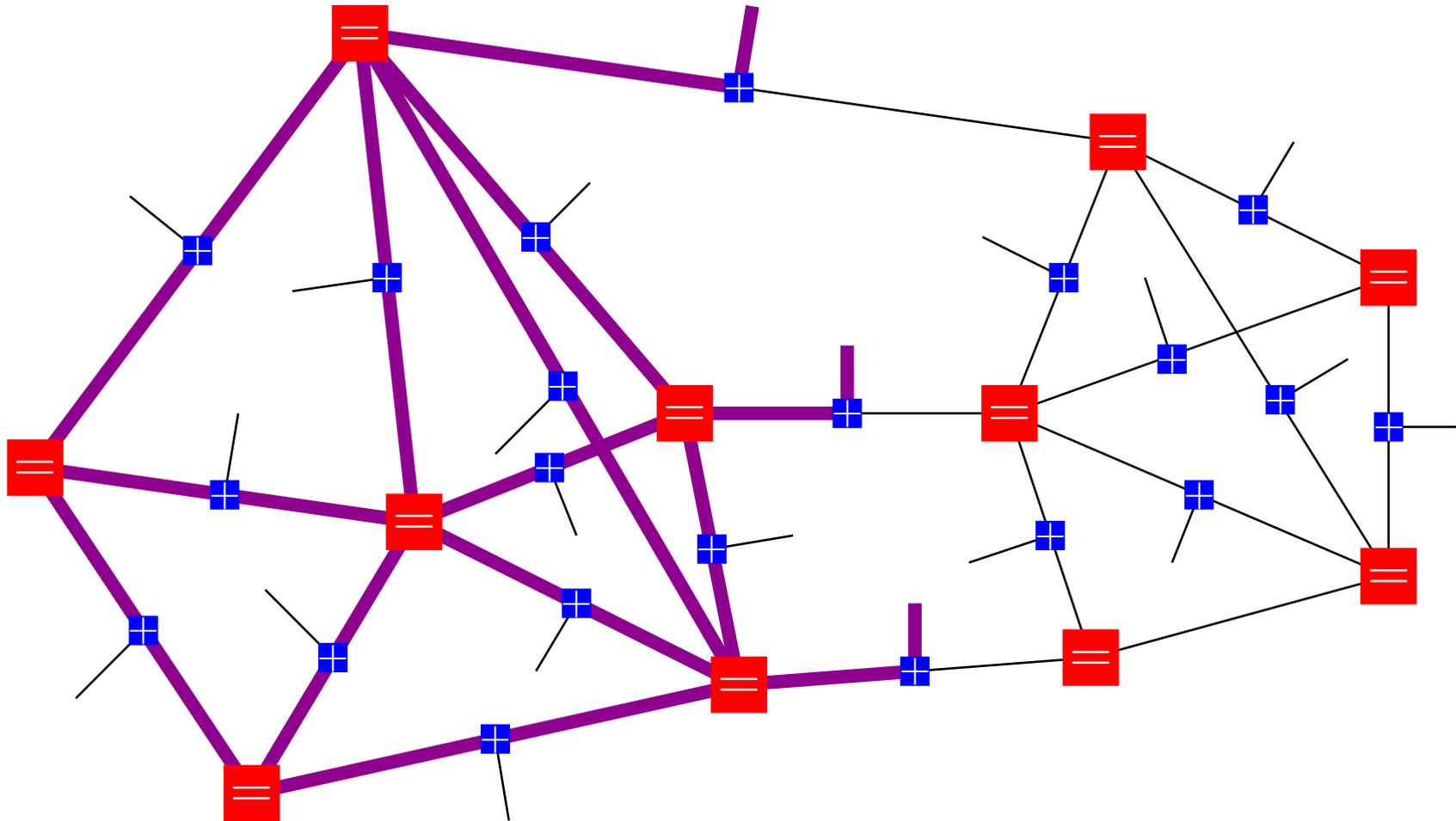
Community Detection in Networks



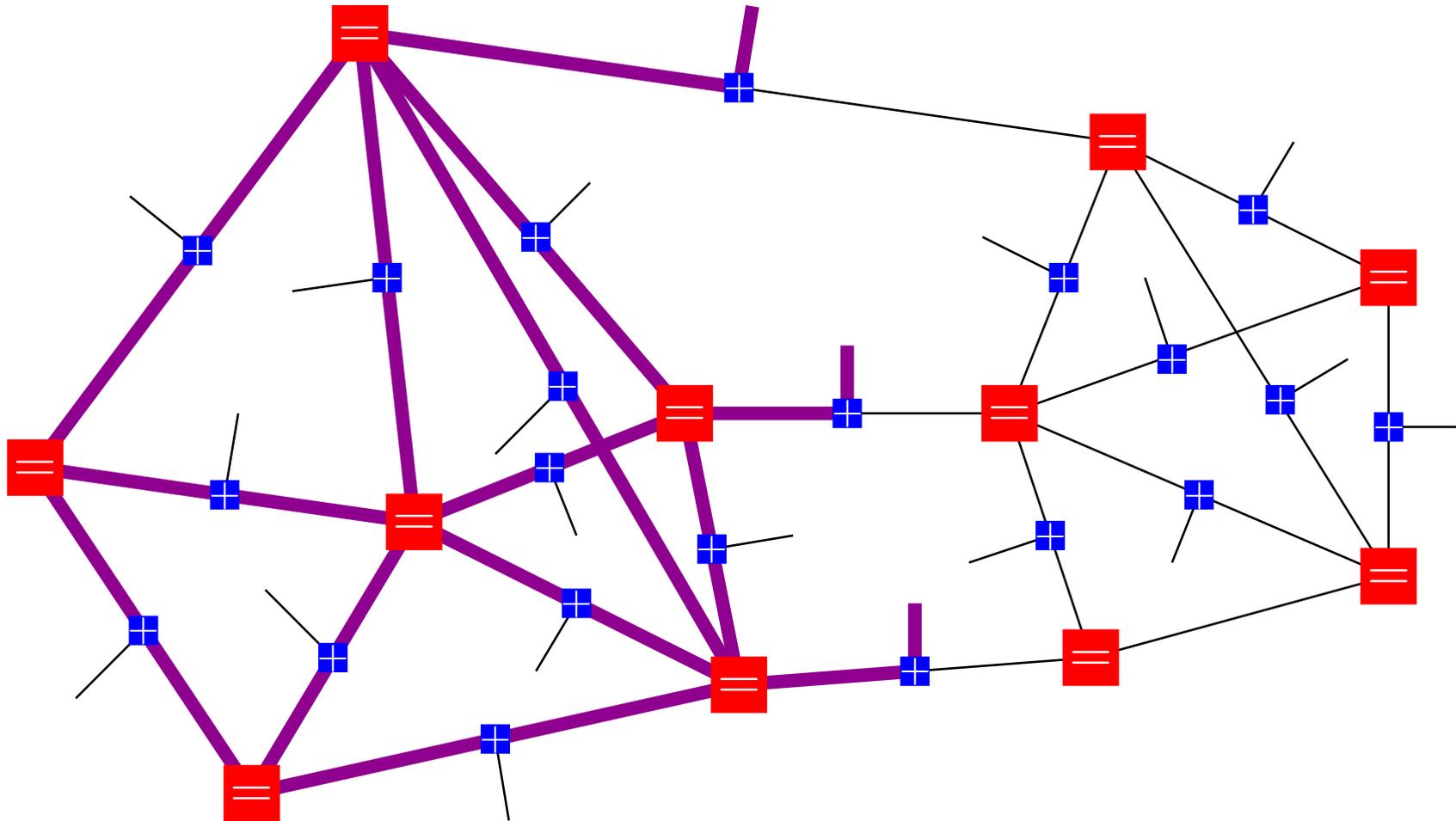
Community Detection in Networks



Community Detection in Networks



Community Detection in Networks

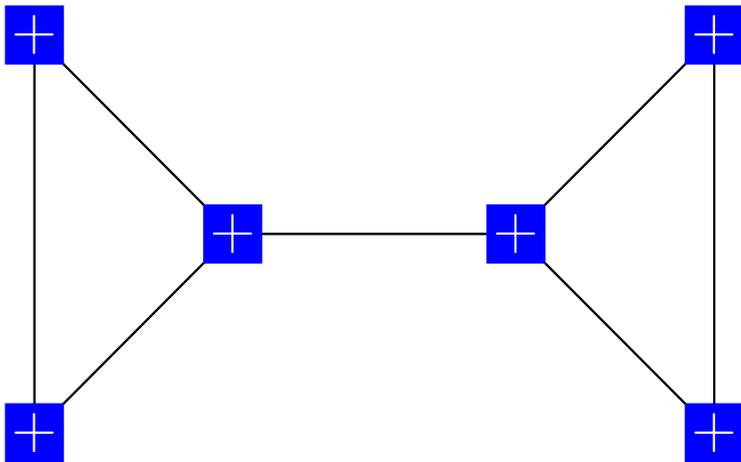


Community detection with the help of MPI algorithms:

[Krzakala, Moore, Mossel, Neeman, Sly, Zdeborová, Zhang, 2013]

Cycle Code NFG vs. Community Detection NFG

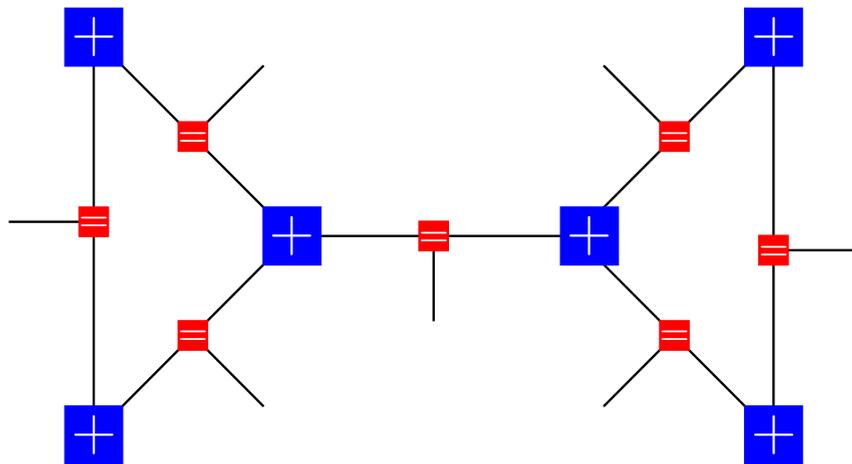
It turns out that the **cycle code normal factor graph** and the **community detection normal factor graph** are **dual to each other** in the sense that the sets of valid configurations are given by dual normal factor graphs, cf. NFG duality in [Forney, 2001].



cycle code
normal factor graph

Cycle Code NFG vs. Community Detection NFG

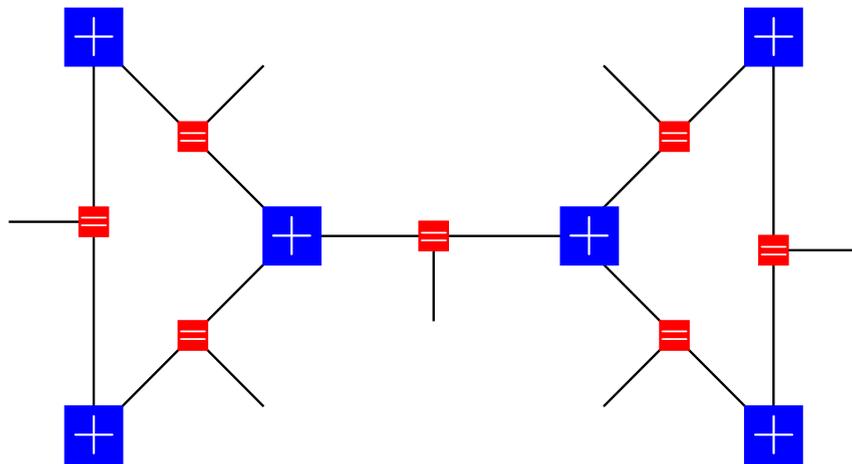
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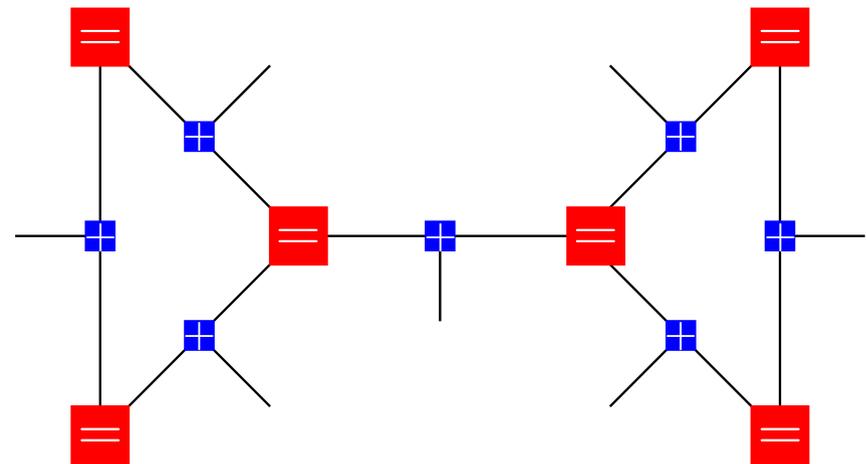
cycle code
normal factor graph

Cycle Code NFG vs. Community Detection NFG

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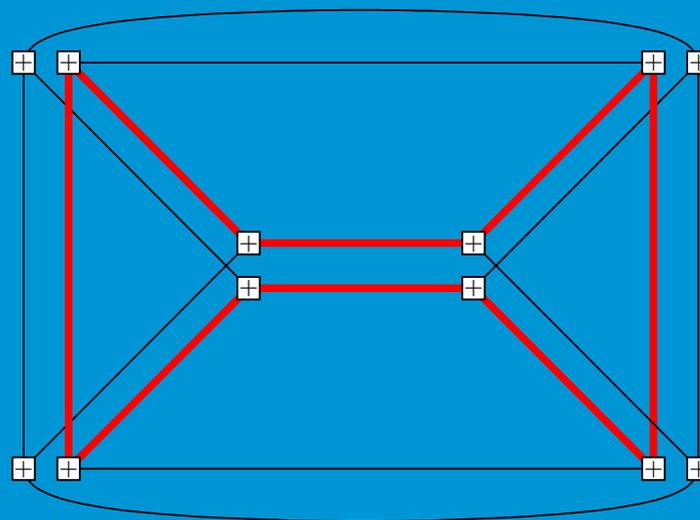
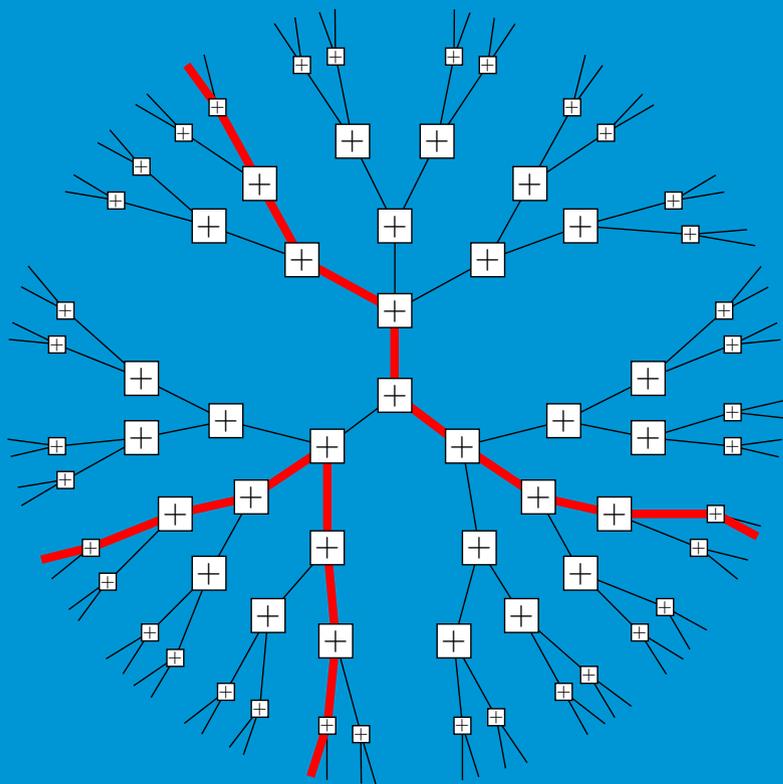
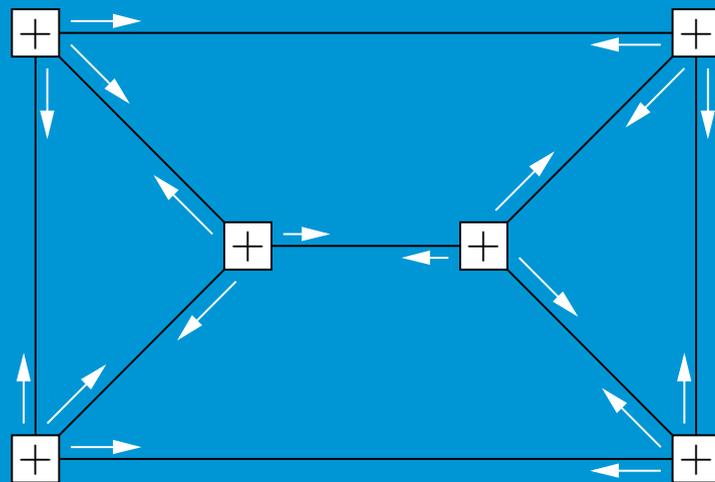


cycle code
normal factor graph



community detection
normal factor graph





$$\zeta(V_1, \dots, V_n) = \sum_{\mathbf{k}} \zeta_{\mathbf{k}} \mathbf{V}^{\mathbf{k}} = \prod_{[\Gamma]} \frac{1}{1 - g(\Gamma, \mathbf{V})}$$

What Can a Power Series Do For You?

Consider the power series $\zeta(\mathbf{V})$:

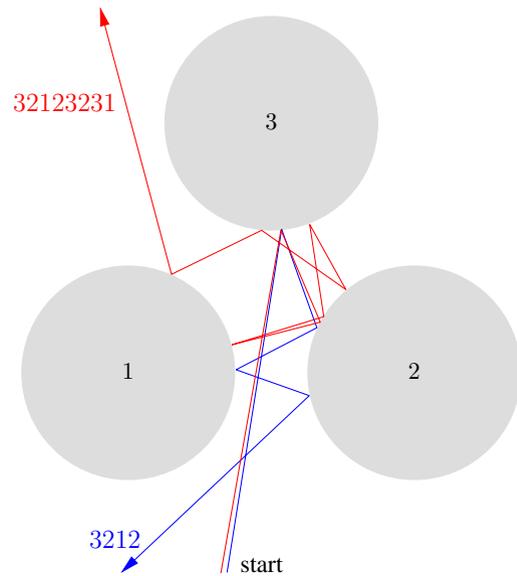
$$\zeta(\mathbf{V}) = \sum_{\mathbf{k}} \zeta_{\mathbf{k}} \mathbf{V}^{\mathbf{k}} = \prod_{[\Gamma]} \frac{1}{1 - g(\Gamma, \mathbf{V})}$$

We can obtain **useful information** from

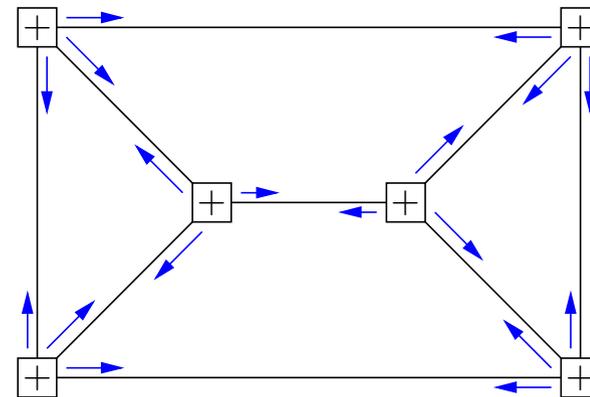
- ... the **expon. vecs.** of $\zeta(\mathbf{V})$ [Koetter, Li, V., Walker, 2004/2007]
- ... the **coefficients** of $\zeta(\mathbf{V})$ [V., 2009/2010] [today]
- ... the **evaluation** of $\zeta(\mathbf{V})$ for some \mathbf{V} [Watanabe, 2009/2010]
- ... the **convergence region** of $\zeta(\mathbf{V})$ [today]
- ...

Use of zeta functions for analyzing graphical models.

Analogy Pinball vs. MPI Decoding



pinball



message-passing iterative decoding
of cycle codes

trajectory

minimal deviation in computation trees

periodic trajectory

codeword in finite graph cover /
graph-cover pseudo-codeword

dynamical edge zeta function

graph zeta function

Pinball

- Ideally, we compute $\hat{\theta}_1, \hat{\theta}_2, \hat{\theta}_3, \dots$, and determine from this γ .
However, usually this is too complicated.
-

- Note that the **power series**

$$\hat{\theta}(z) = \sum_{n=1}^{\infty} \hat{\theta}_n z^n$$

has **convergence radius** $\exp(\gamma)$.

- Alternative approach: set up a **new power series**

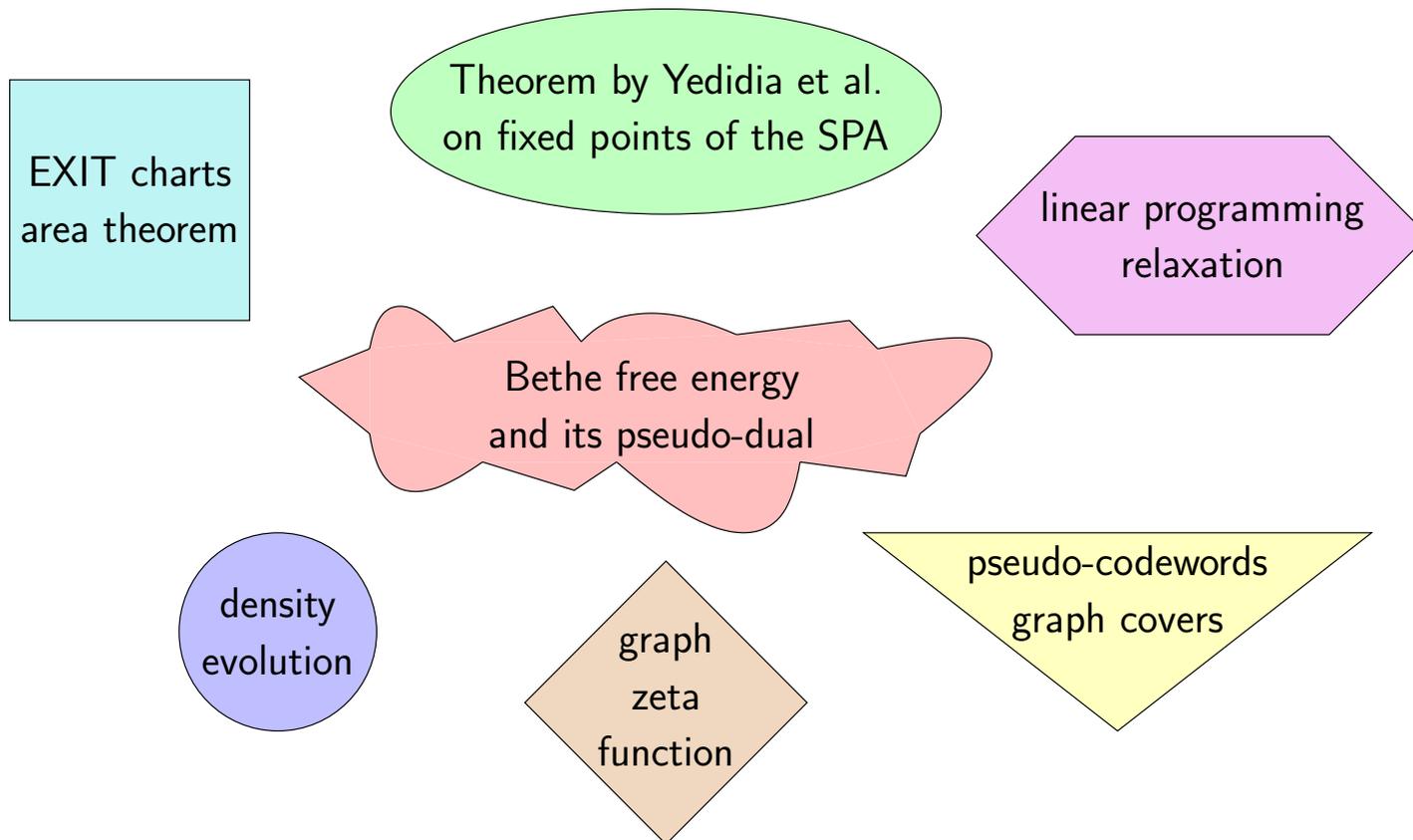
$$\theta(z) = \sum_{n=1}^{\infty} \theta_n z^n$$

so that its **convergence radius** equals $\exp(\gamma)$.

Bethe Free Energy Function

Some of the properties of the **Bethe free energy function** of the cycle code normal factor graph:

- The induced Bethe free energy function is a **convex**.
- The sum-product algorithm **finds its minimum**.



Comments

- We have some **generalizations** of the above results to **general LDPC codes** under **attenuated SPA decoding**.
- Note that **[Watanabe, 2010]** connects **zeta function values** to the **Hessian of the Bethe free energy function** for **general factor graphs**.
- Use of other concepts from **chaos theory** for understanding graphical models:
 - Agrawal and Vardy, “**The turbo decoding algorithm and its phase trajectories,**” IEEE Trans. Inf. Theory, 2001.
 - Kocarev, Lehmann, Maggio, Scanavino, Tasev, and Vardy, “**Nonlinear dynamics of iterative decoding systems: analysis and applications,**” IEEE Trans. Inf. Theory, 2006.
 - ...

References

H. D. Pfister and P. O. Vontobel, “On the relevance of graph covers and zeta functions for the analysis of SPA decoding of cycle codes,” Proc. ISIT 2013. (A longer version of this paper is in preparation.)

This work uses and extends results from:

- P. O. Vontobel, “Counting in graph covers: a combinatorial characterization of the Bethe entropy function,” IEEE Trans. Inf. Theory, vol. 59, no 9, pp. 6018–6048, Sep. 2013.
- P. O. Vontobel, “The Bethe permanent of a non-negative matrix,” IEEE Trans. Inf. Theory, vol. 59, no. 3, pp. 1866–1901, Mar. 2013.

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Thank you!

