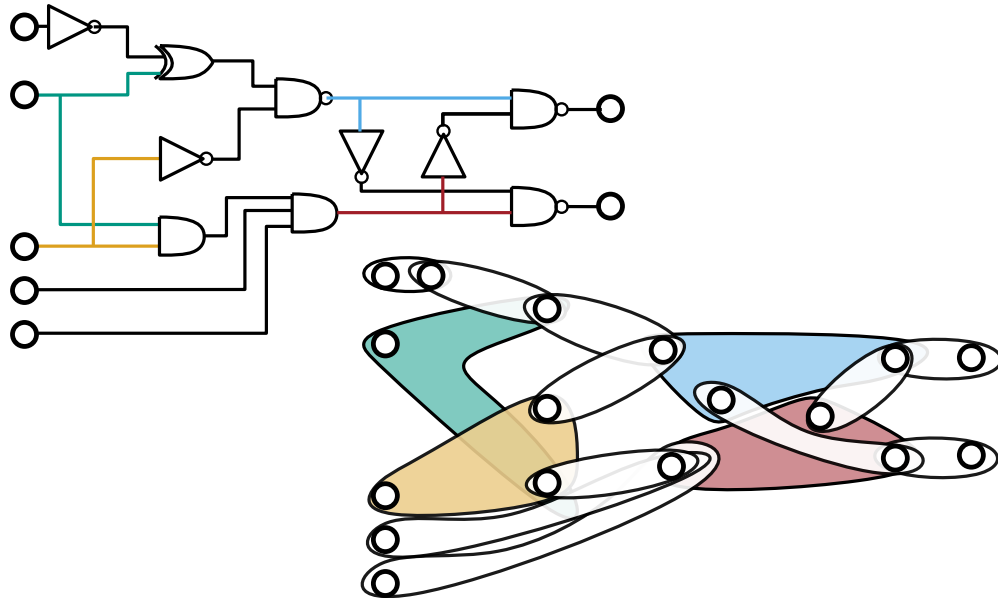


# High Quality Hypergraph Partitioning via Max-Flow-Min-Cut Computations

Master Thesis · February 16, 2018  
Tobias Heuer

INSTITUTE OF THEORETICAL INFORMATICS · ALGORITHMICS GROUP



## Task

Developing a **local search** algorithm based on **Max-Flow-Min-Cut** computations for the  $n$ -level hypergraph partitioner **KaHyPar**.

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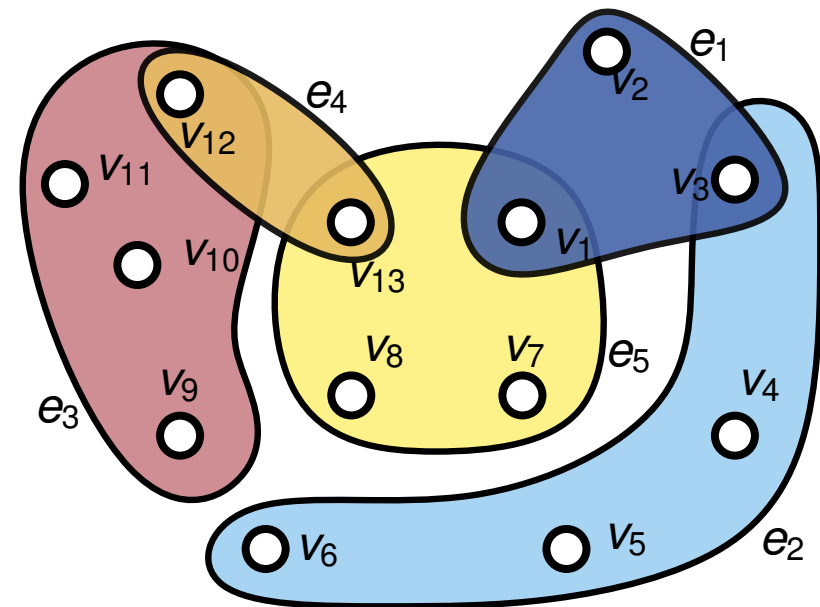
## Contributions

- Outperforms 5 different systems on 73% of 3216 benchmark instances
- Improve quality of *KaHyPar* by 2.5%, while only incurring a slowdown by a factor of 2
- Comparable running time to *hMetis* and outperforms it on 84% of the instances

# Hypergraphs

[from SEA'17]

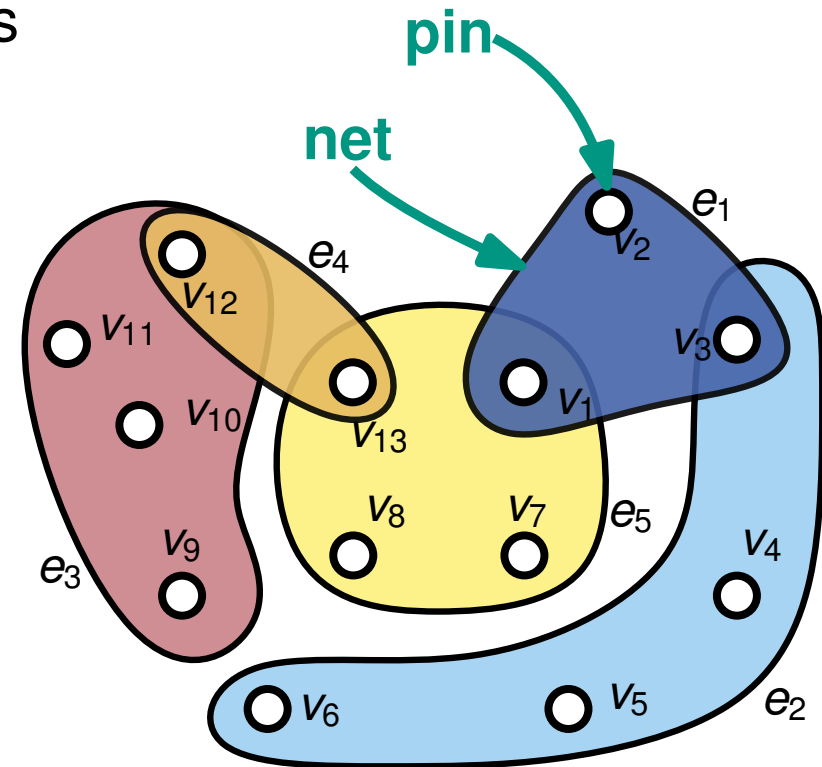
- Generalization of graphs  
 $\Rightarrow$  hyperedges connect  $\geq 2$  nodes
- Graphs  $\Rightarrow$  dyadic (**2-ary**) relationships
- Hypergraphs  $\Rightarrow$  (**d-ary**) relationships
- Hypergraph  $H = (V, E, c, \omega)$ 
  - Vertex set  $V = \{1, \dots, n\}$
  - Edge set  $E \subseteq \mathcal{P}(V) \setminus \emptyset$
  - Node weights  $c : V \rightarrow \mathbb{R}_{\geq 1}$
  - Edge weights  $\omega : E \rightarrow \mathbb{R}_{\geq 1}$



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- $|P| = \sum_{e \in E} |e| = \sum_{v \in V} d(v)$



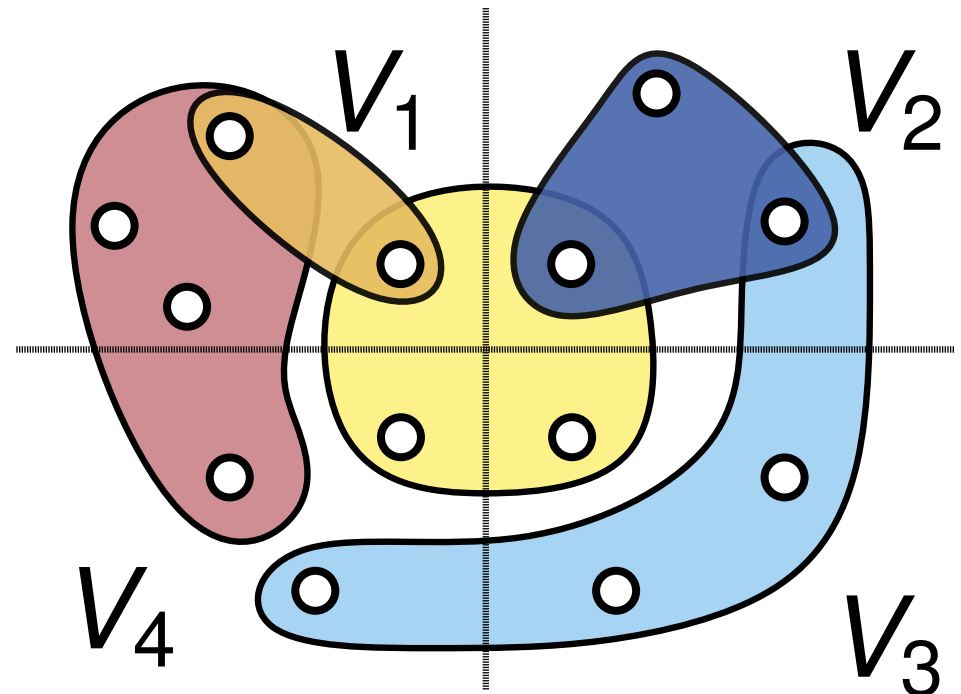
# Hypergraph Partitioning Problem

[from SEA'17]

Partition hypergraph  $H = (V, E, c, \omega)$  into  $k$  non-empty disjoint blocks  $\Pi = \{V_1, \dots, V_k\}$  such that:

- blocks  $V_i$  are **roughly equal-sized**:

$$c(V_i) \leq (1 + \varepsilon) \left\lceil \frac{c(V)}{k} \right\rceil$$



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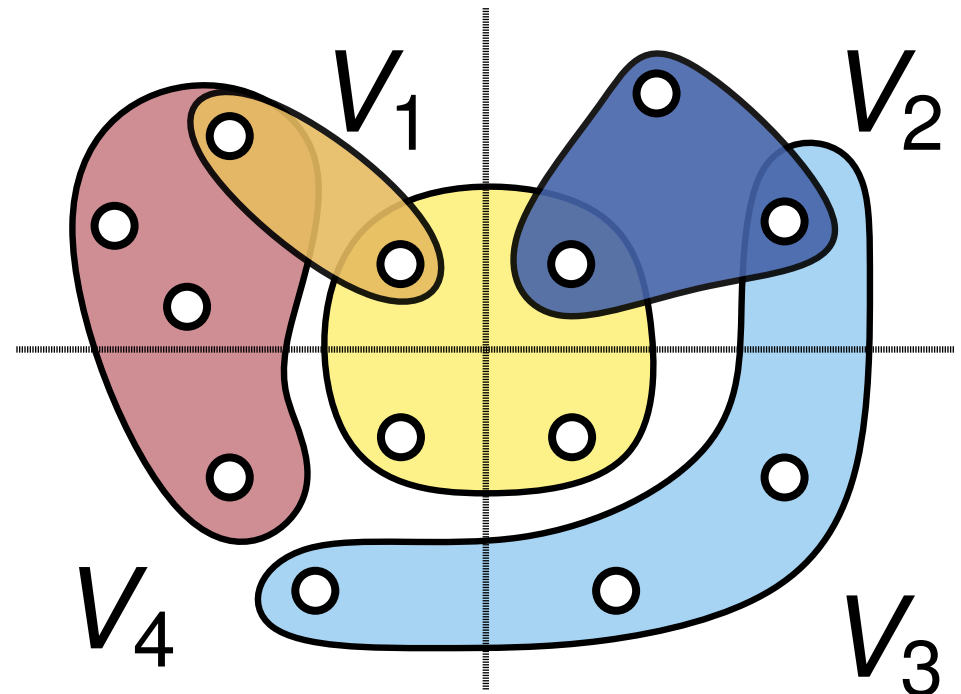
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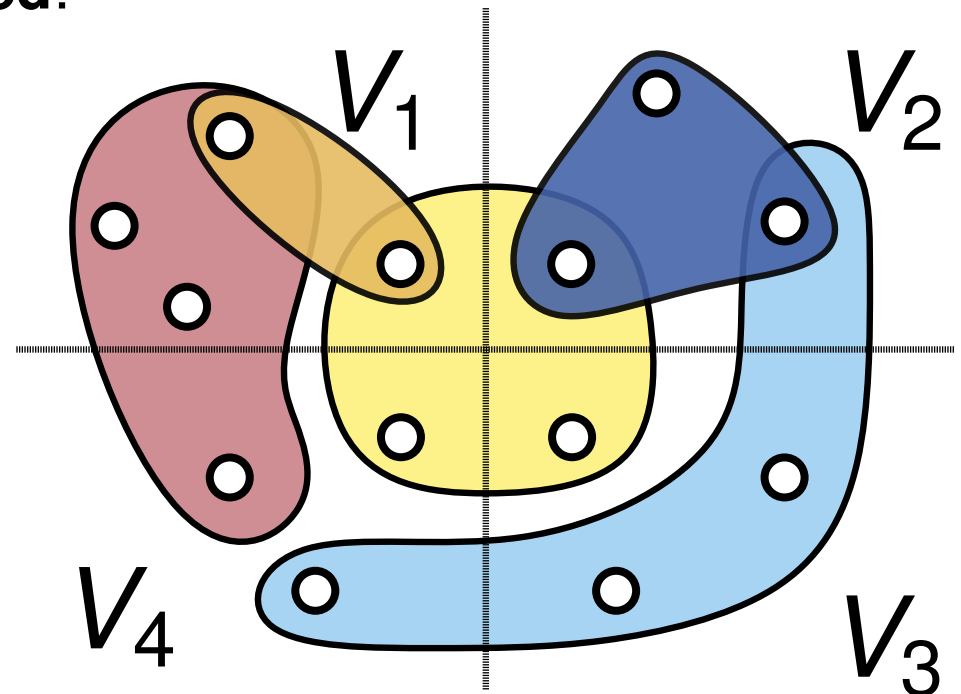
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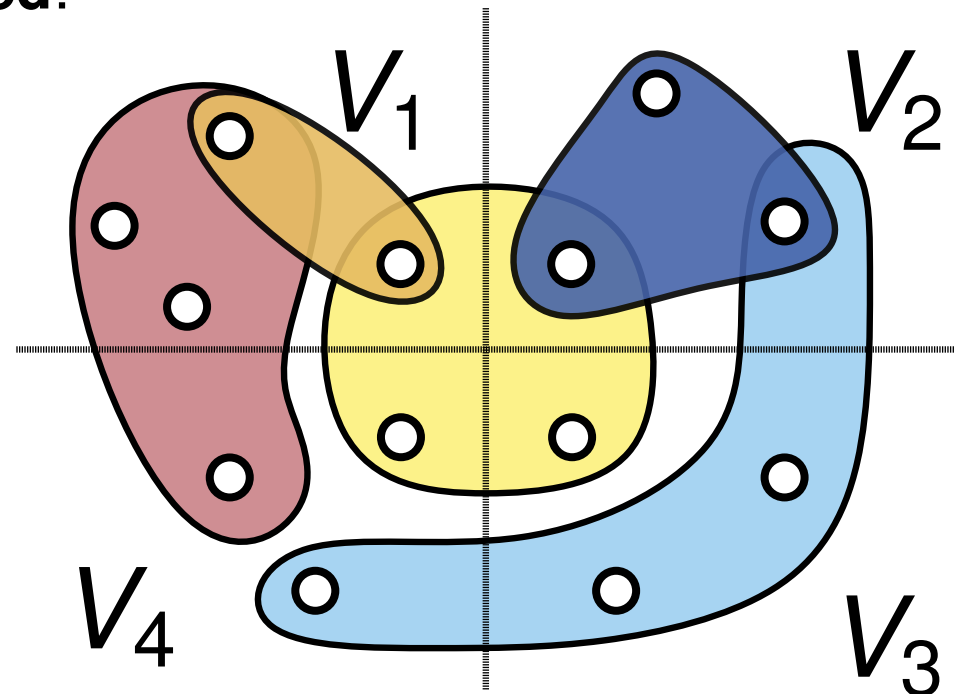
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# **blocks** connected by net  $e$



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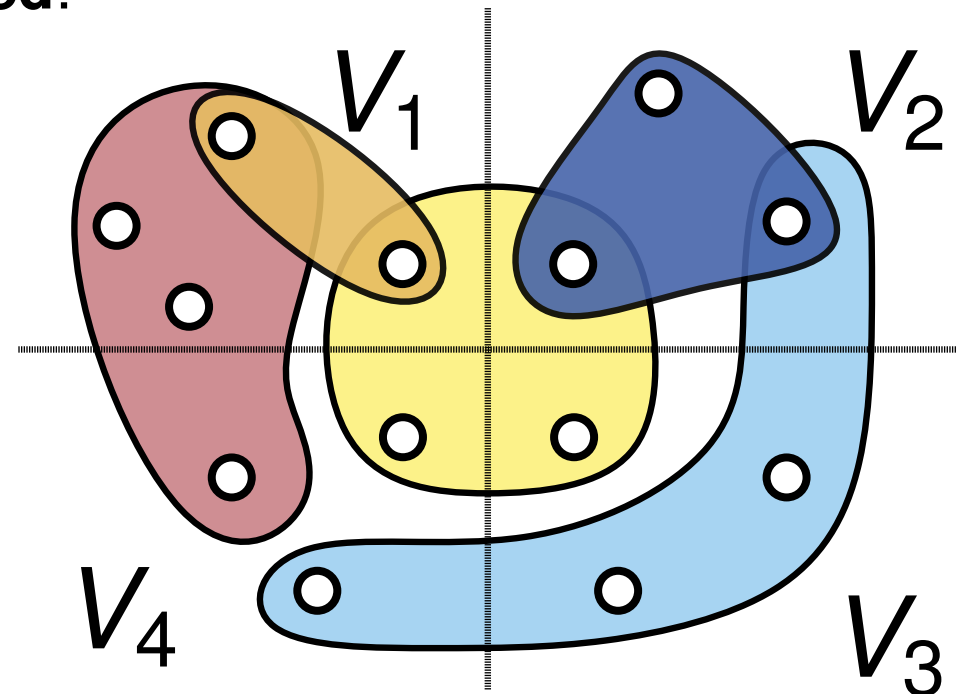
$$c(V_i) \leq (1 + \varepsilon) \left\lceil \frac{c(V)}{k} \right\rceil$$

**imbalance  
parameter**

- **connectivity** objective is **minimized**:

$$\sum_{e \in \text{cut}} (\lambda - 1) \omega(e) = 6$$

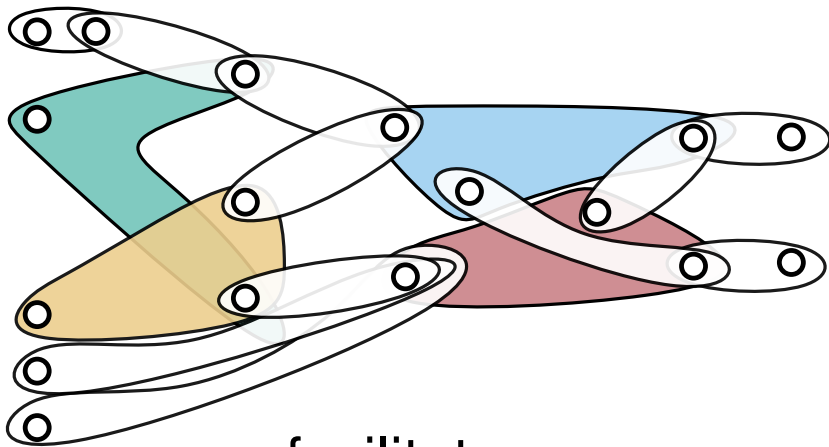
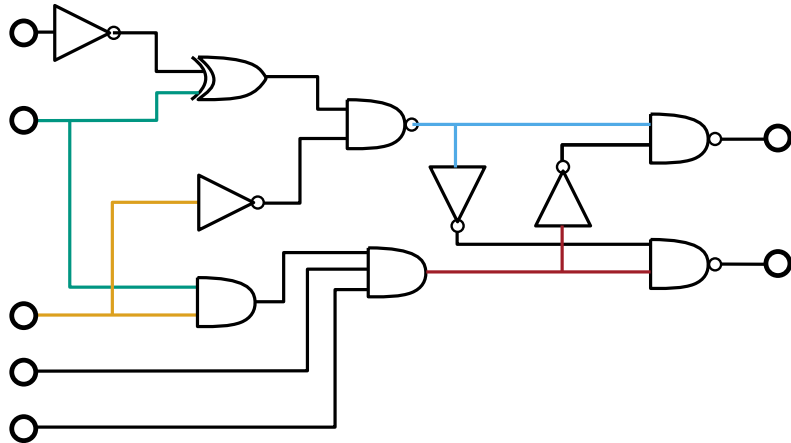
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# Applications

[from SEA'17]

## VLSI Design



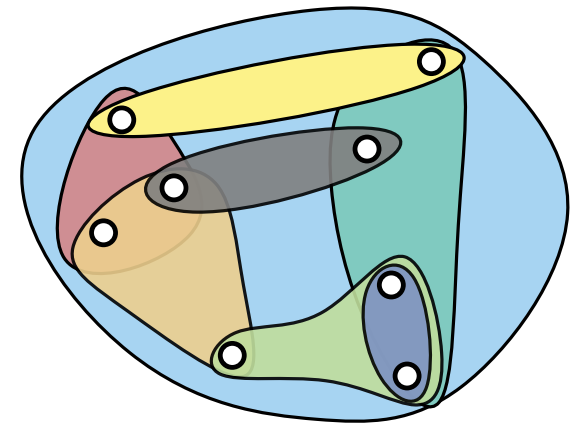
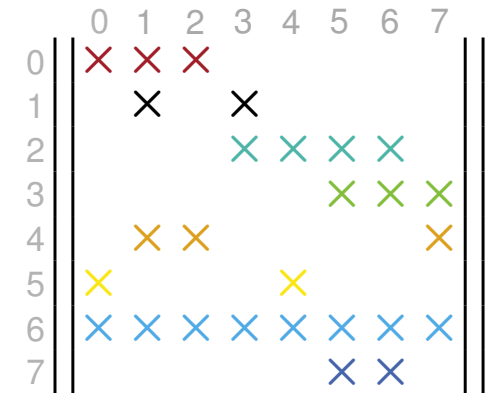
facilitate  
floorplanning & placement

Application  
Domain

Hypergraph  
Model

Goal

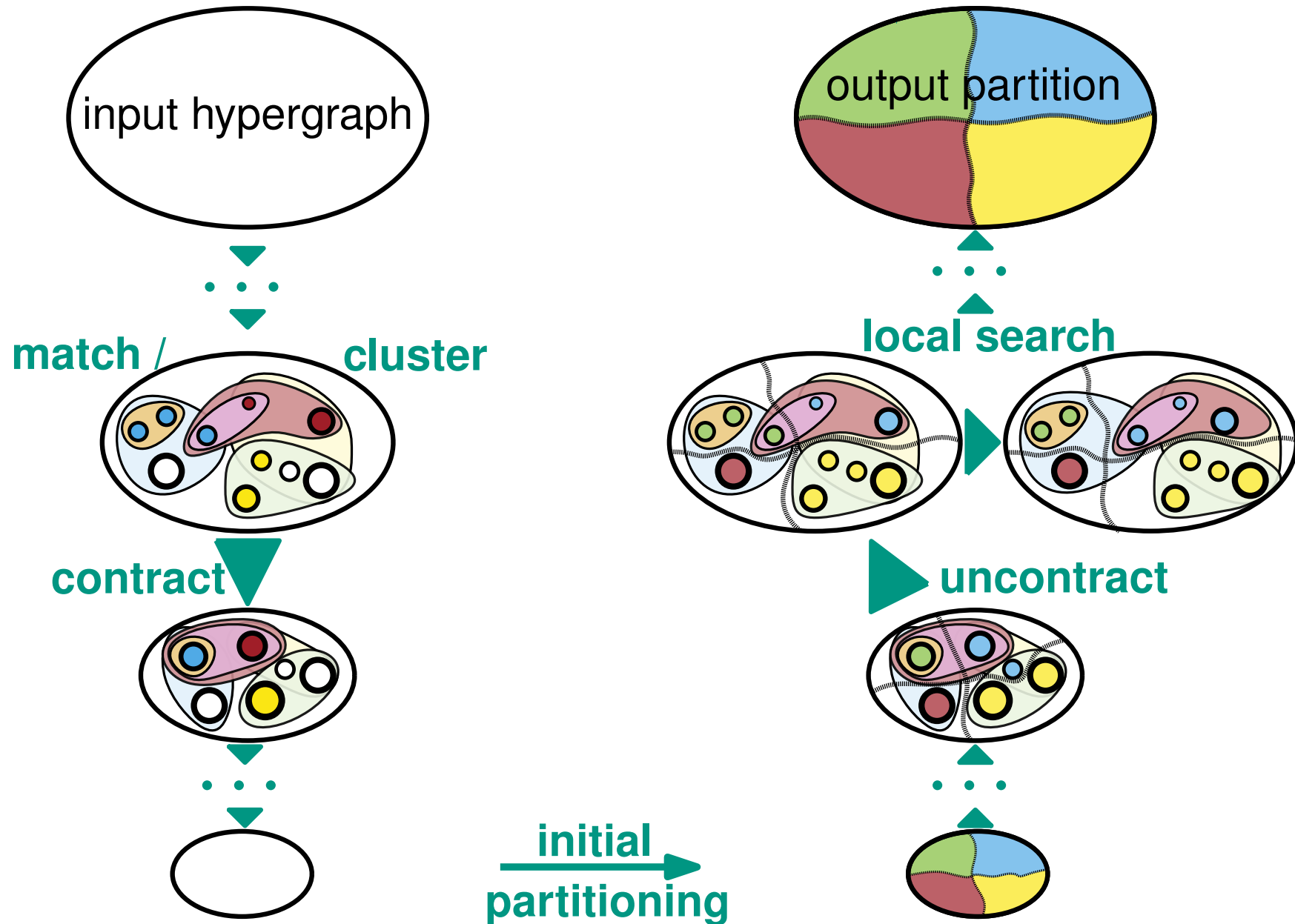
## Scientific Computing



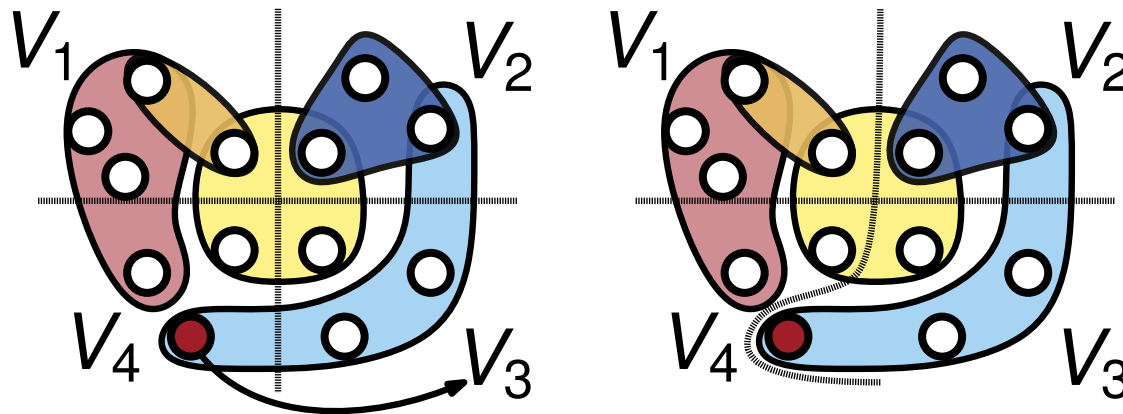
minimize  
communication

# The Multilevel Framework

[from SEA'17]

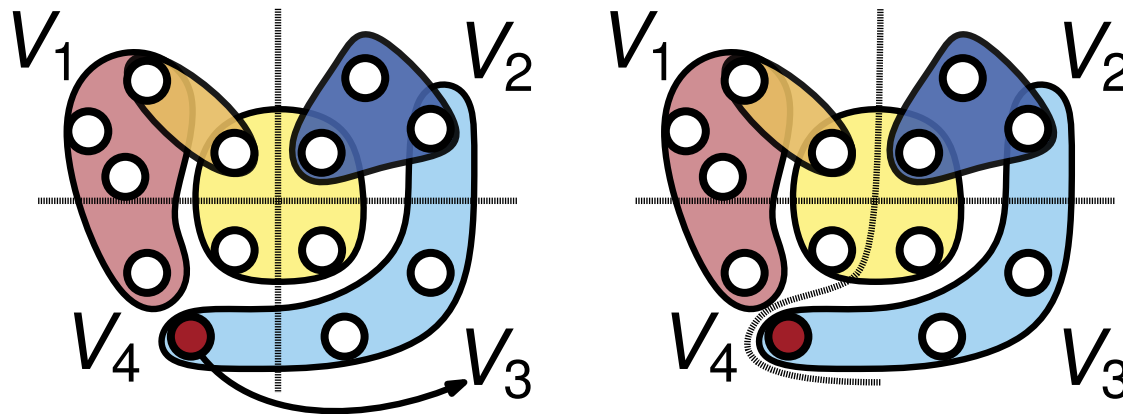


- **Move**-based heuristic that **greedily** move vertices between blocks based on **local** informations of incident nets



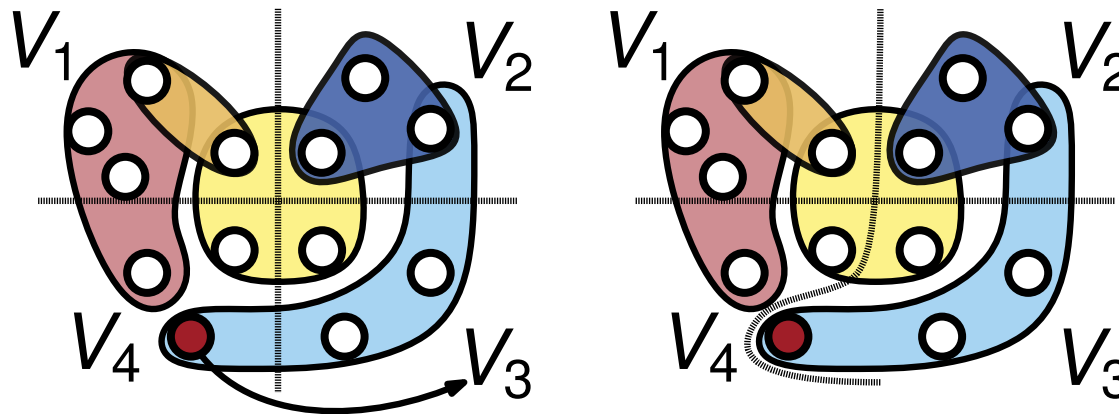
Moving ● from  $V_4$  to  $V_3$  reduces cut by 1

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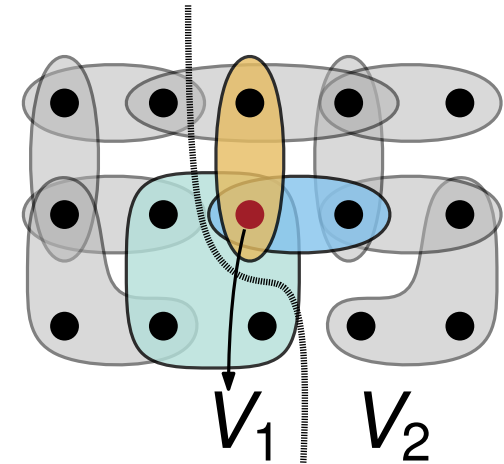
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gain 

- Performs moves of vertices with **maximum gain** in each step
- All modern hypergraph partitioners implements variations of the *FM* algorithm

# FM Algorithm - Disadvantages

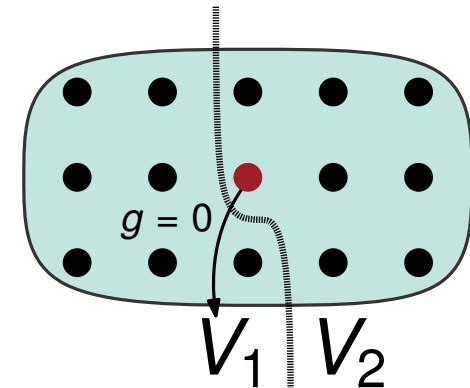
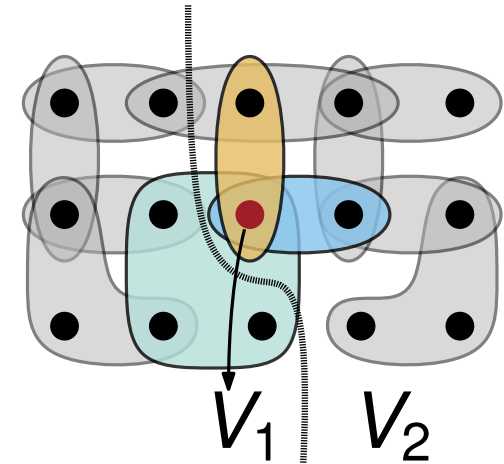
- Only incorporates **local** informations about the problem structure
- Heavily depends on *initial partition*
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# FM Algorithm - Disadvantages

- Only incorporates **local** informations about the problem structure
  - Heavily depends on *initial partition*
  - In multilevel context: Depends on quality of *coarsening*
- 
- Large hyperedges induce **Zero-Gain** moves
  - Quality mainly depends on random decisions made within the algorithm



# Flow-based Approaches

# Flows

Given a graph  $G = (V, E, u)$  and two nodes  $s, t \in V$

- $u : E \rightarrow \mathbb{R}_+$  is the **capacity** function
- $s$  and  $t$  are called **source** and **sink**

# Flows

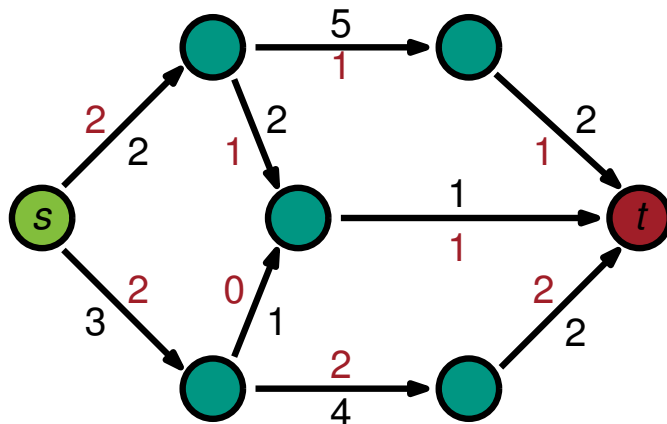
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A valid **flow** is a function  $f : E \rightarrow \mathbb{R}_+$  with the constraints:

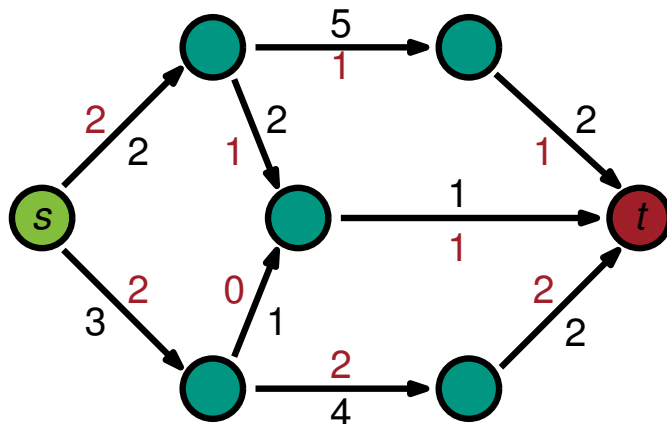
- $\forall (v, w) \in E : f(v, w) \leq u(v, w)$
- $\forall v \in V \setminus \{s, t\} : \sum_{(w, v) \in E} f(w, v) = \sum_{(v, w) \in E} f(v, w)$

The value of the flow is  $|f| = \sum_{(s, v) \in E} f(s, v)$



The **residual capacity**  $r_f : V \times V \rightarrow \mathbb{R}_+$  is defined as follows:

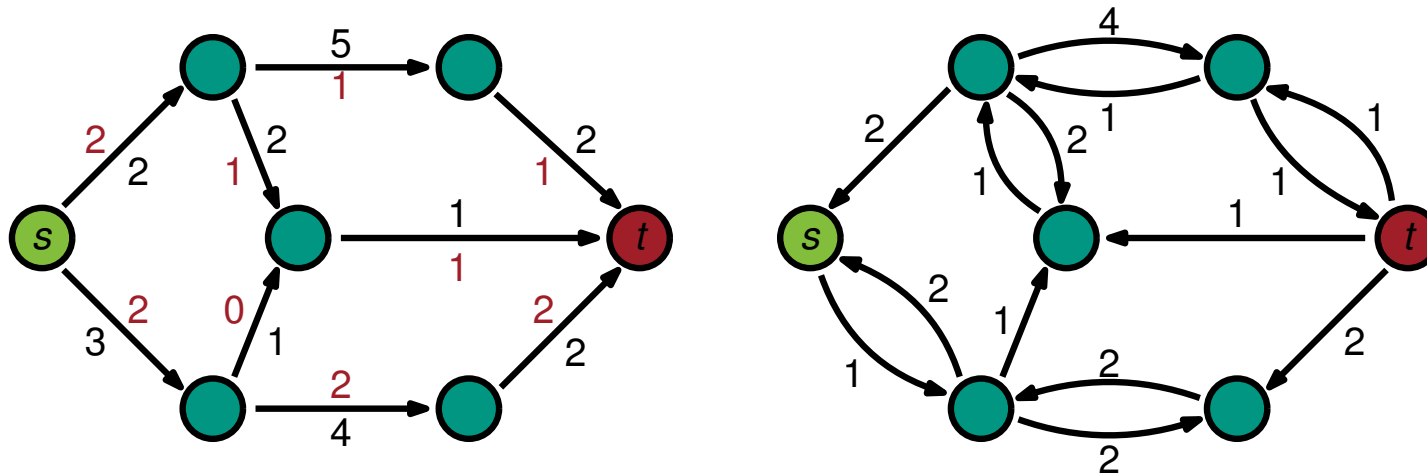
- $\forall (v, w) \in E : r_f(v, w) = u(v, w) - f(v, w)$
- $\forall (v, w) \in E : \text{If } f(v, w) > 0 \text{ and } u(w, v) = 0, \text{ then } r_f(w, v) = f(v, w)$



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The **residual graph**  $G_f = (V, E_f, r_f)$  contains all edges  $(v, w) \in V \times V$  with  $r_f(v, w) > 0$

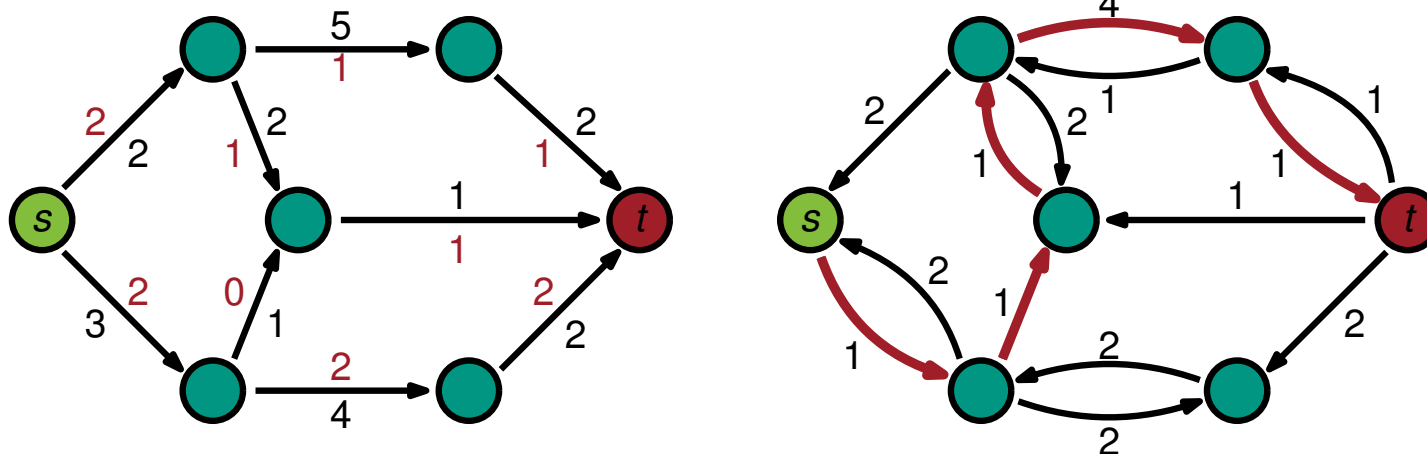


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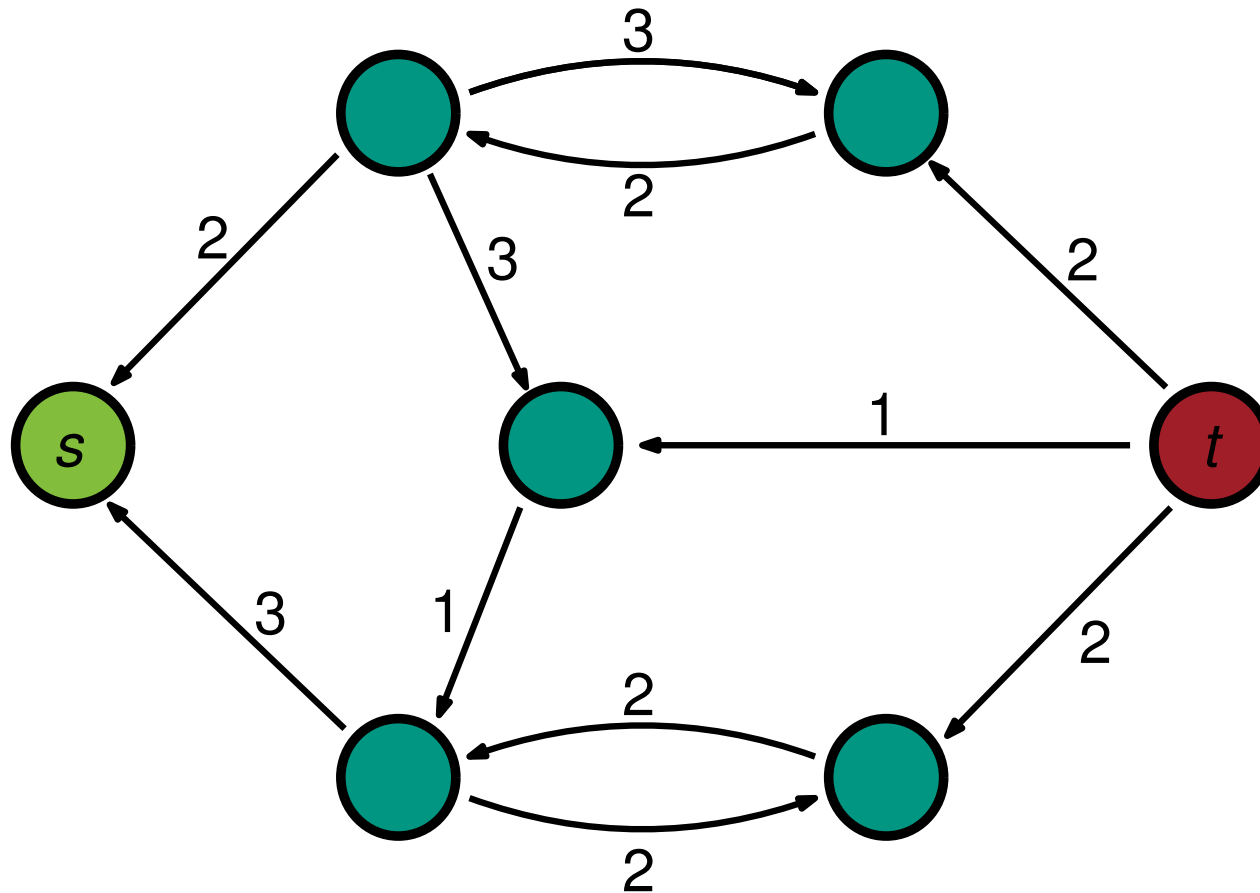
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- An **augmenting path** is a path in  $G_f$  from  $s$  to  $t$
- $f$  is a **maximum flow**, if there is no augmenting path from  $s$  to  $t$  in  $G_f$



# Minimum $(s, t)$ -Bipartition

All nodes *reachable* from  $s$  are part of  $V_1$  and  $V_2 = V \setminus V_1$

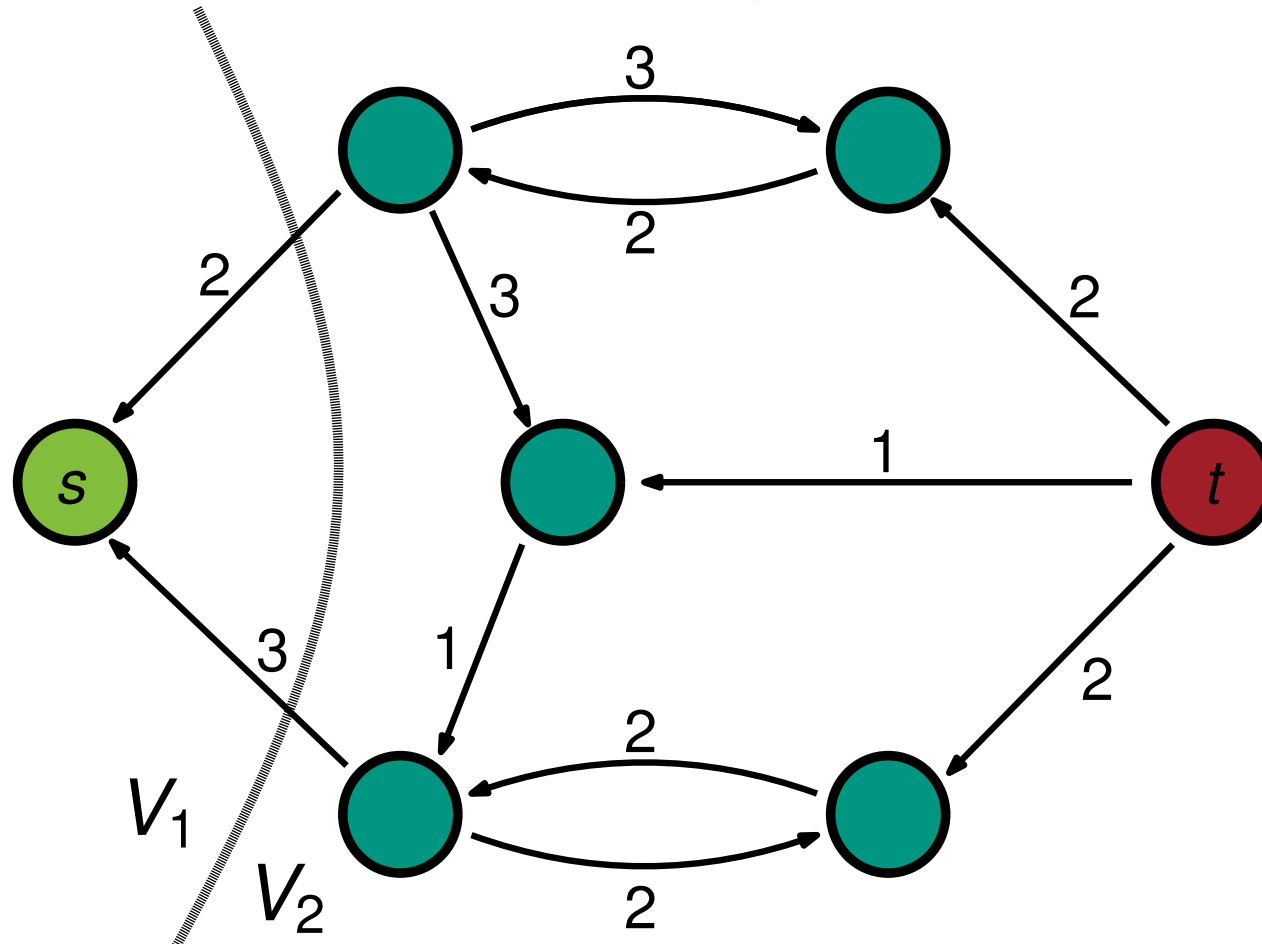


Residual Graph  $G_f$  of a maximum flow  $f$



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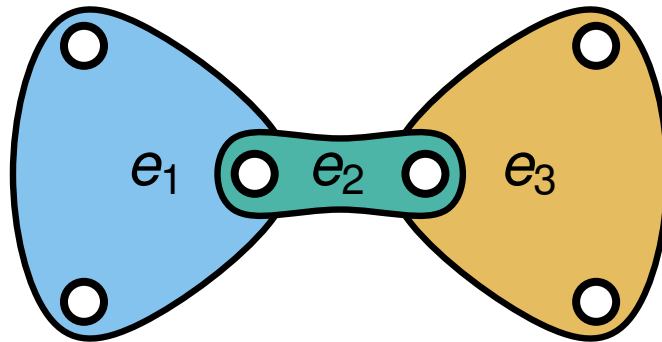
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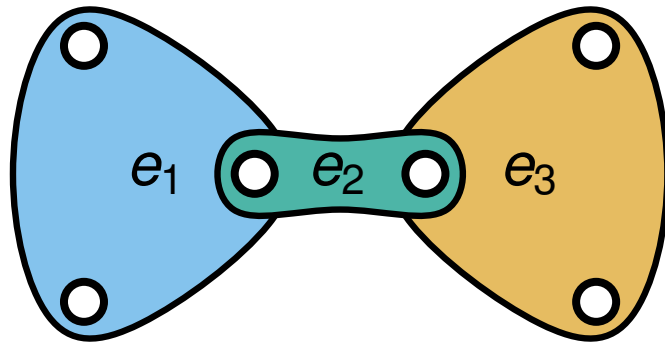
# Hypergraph Flow Network

Hypergraph  $H$

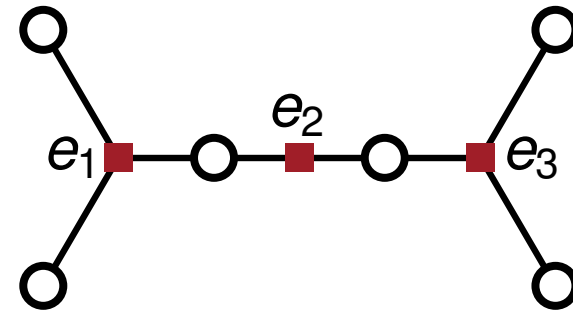


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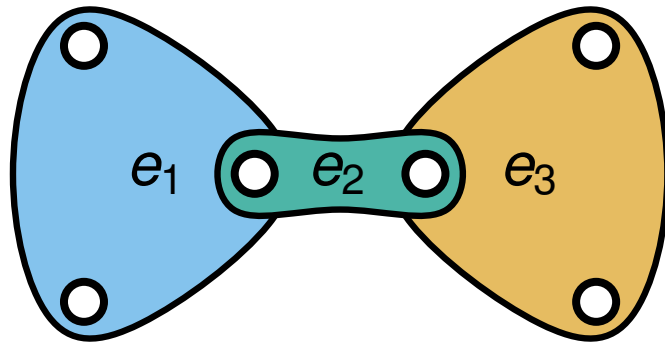


Bipartite Graph  $G_*(H)$

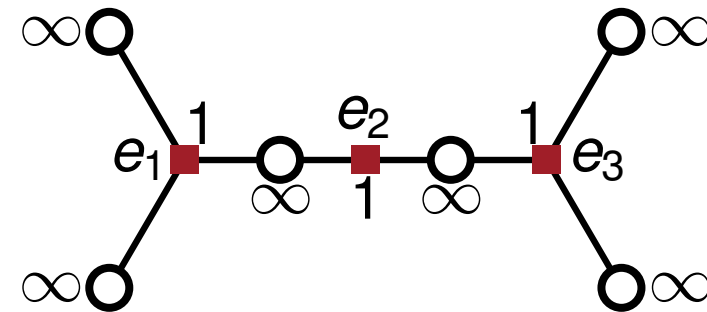


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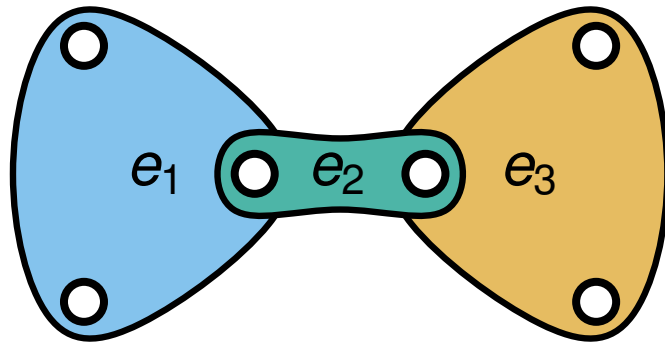
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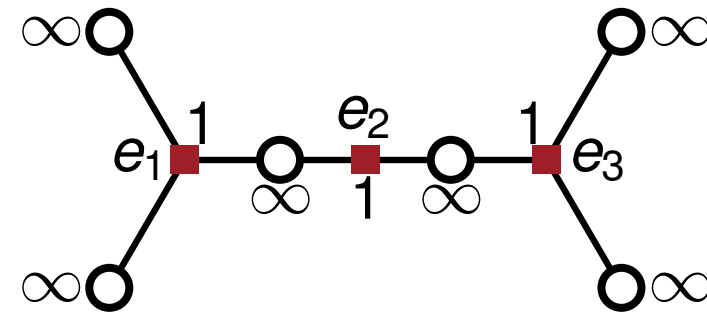
Vertex Separator Problem

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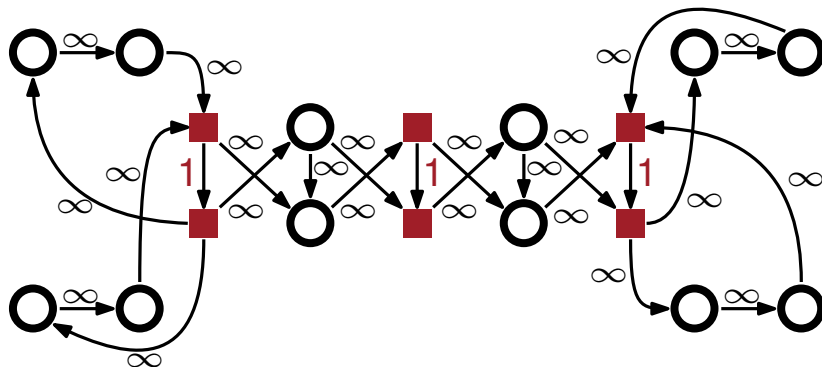


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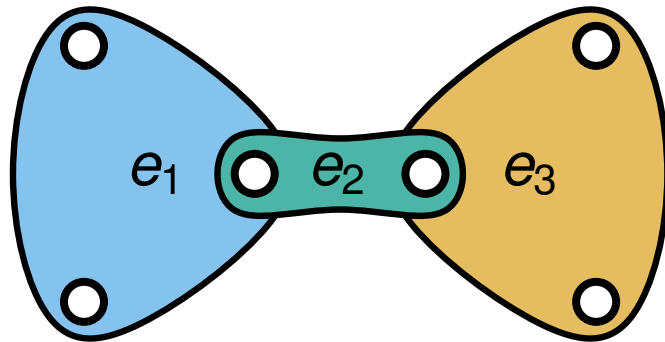
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Vertex Separator Transformation

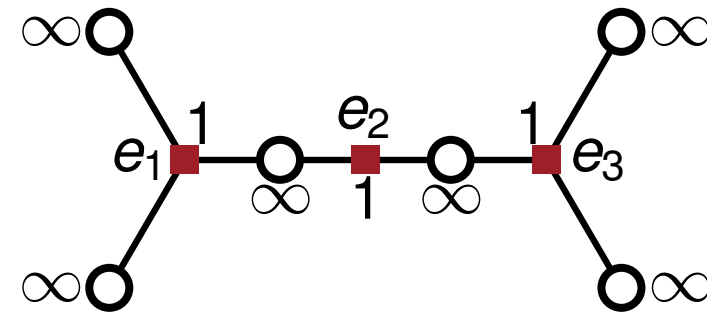


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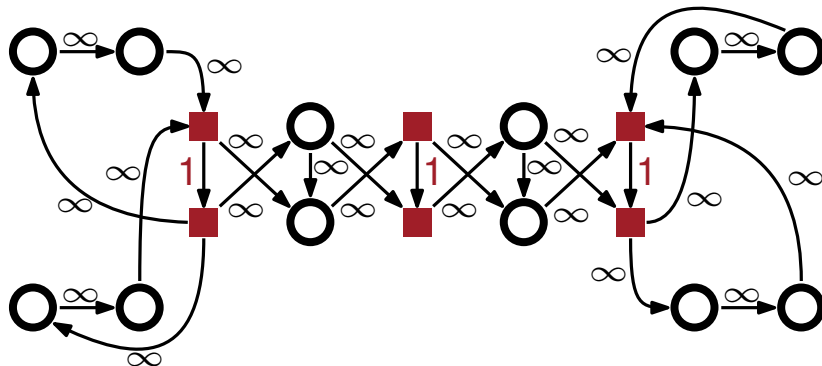


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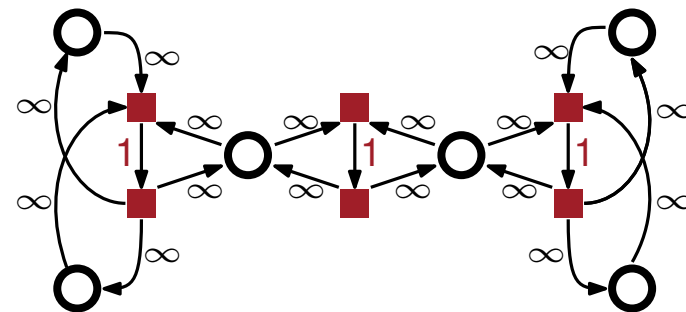


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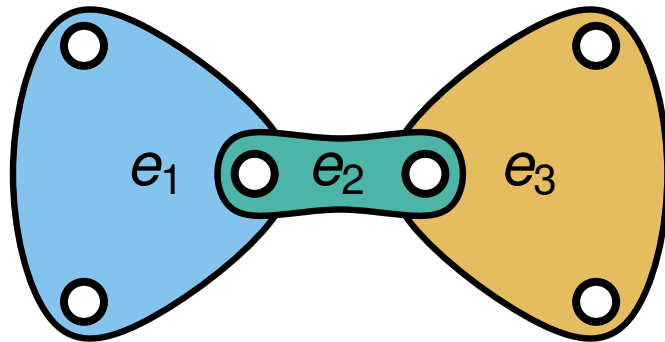


Lawler Network

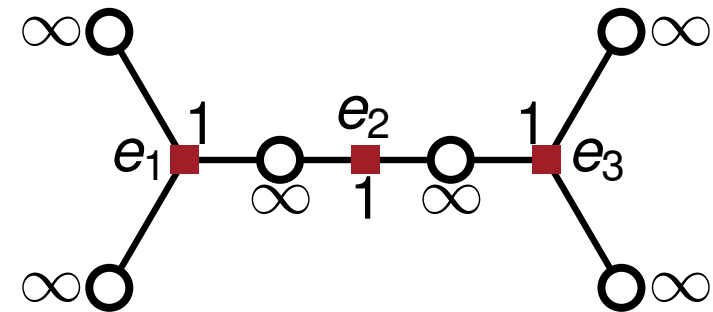


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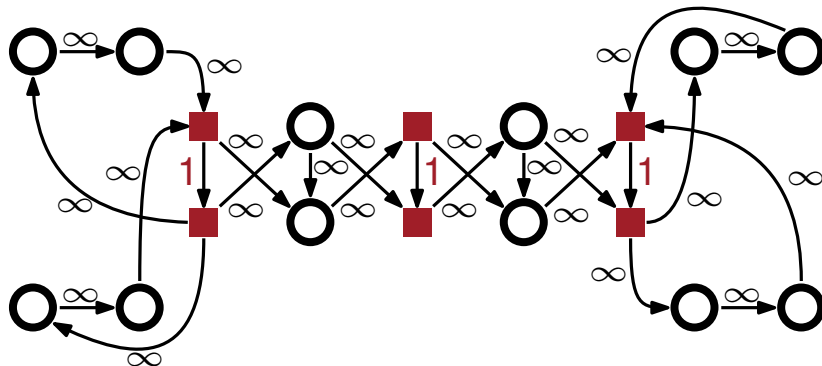


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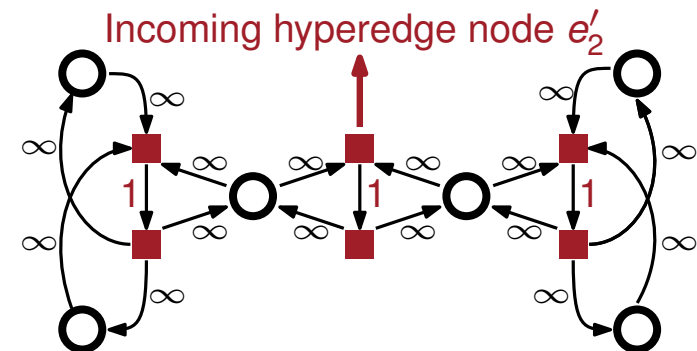


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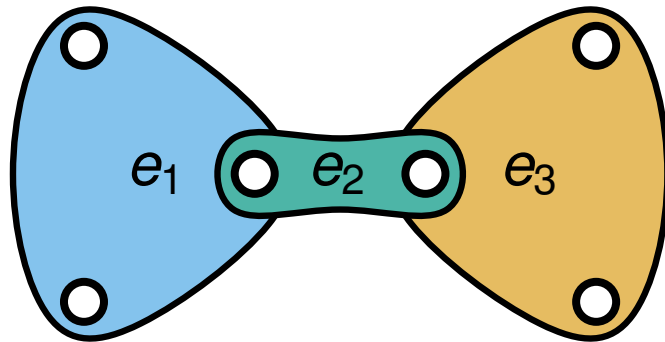


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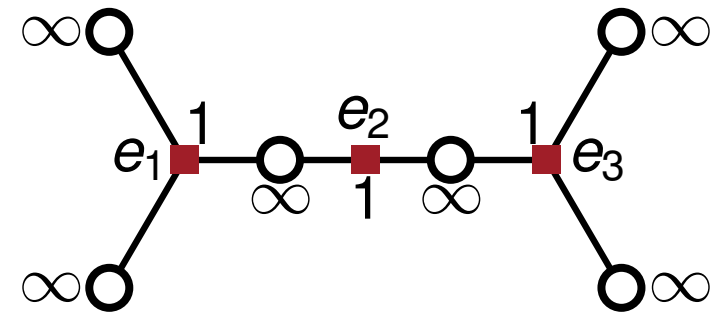


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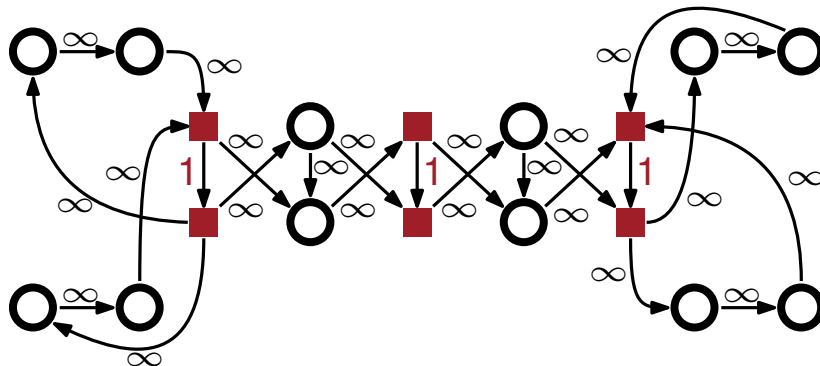


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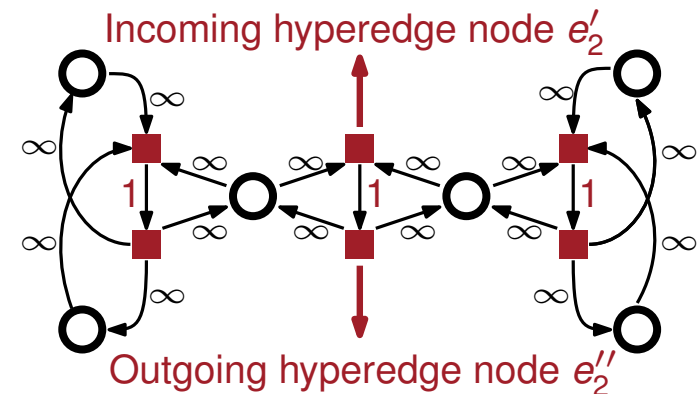


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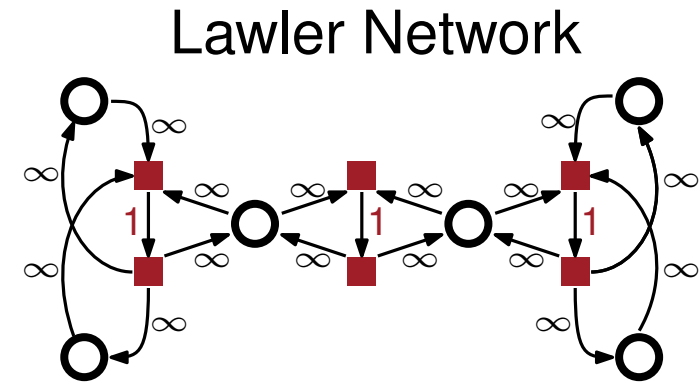
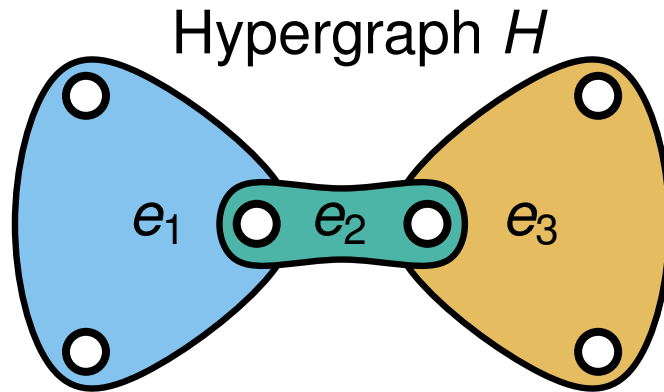


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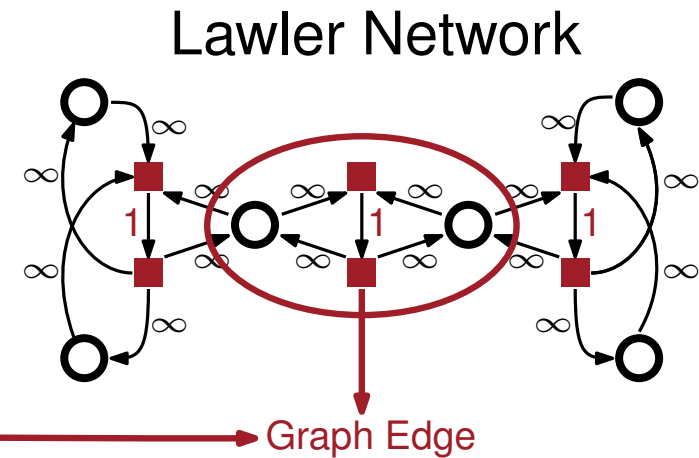
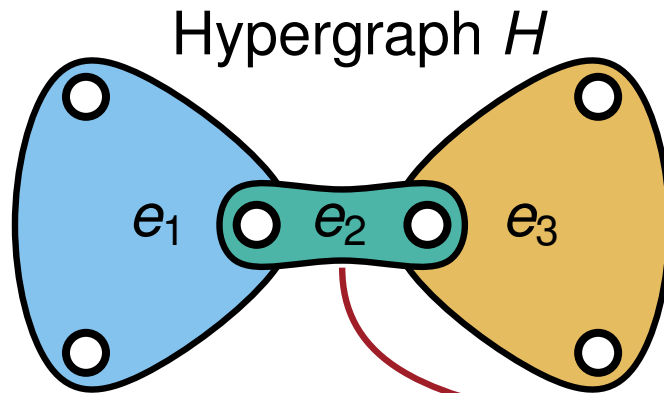




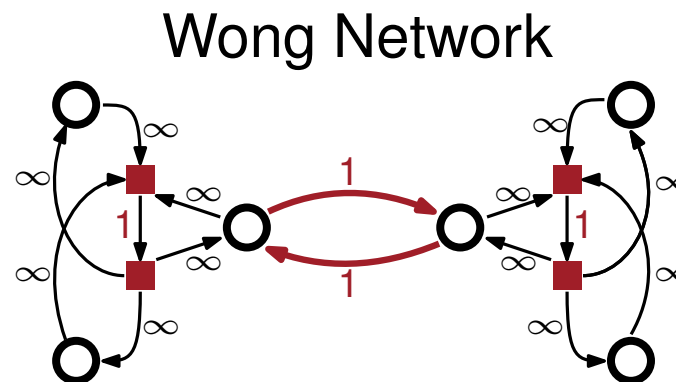
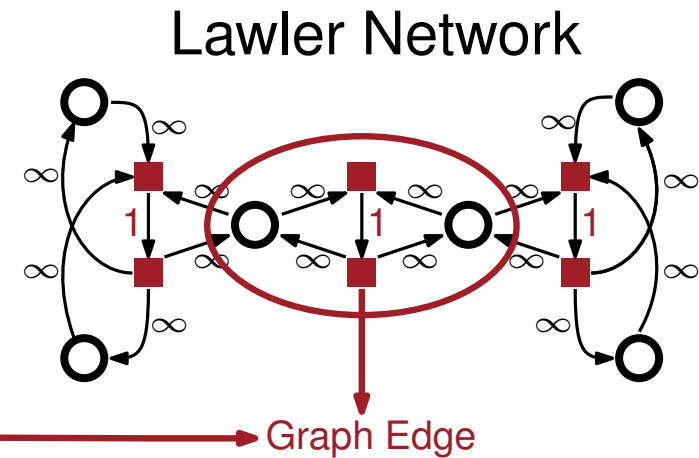
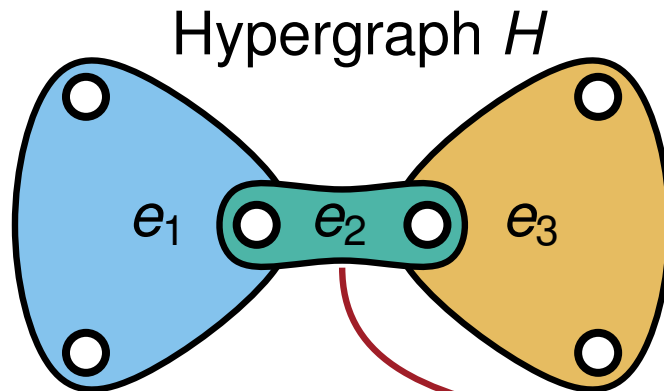
# Hypergraph Flow Network - Graph Edges



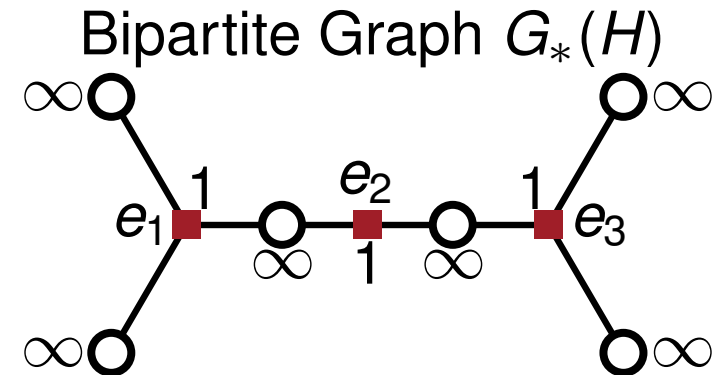
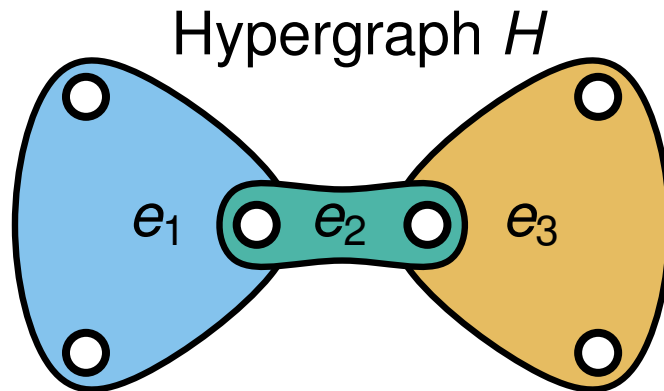
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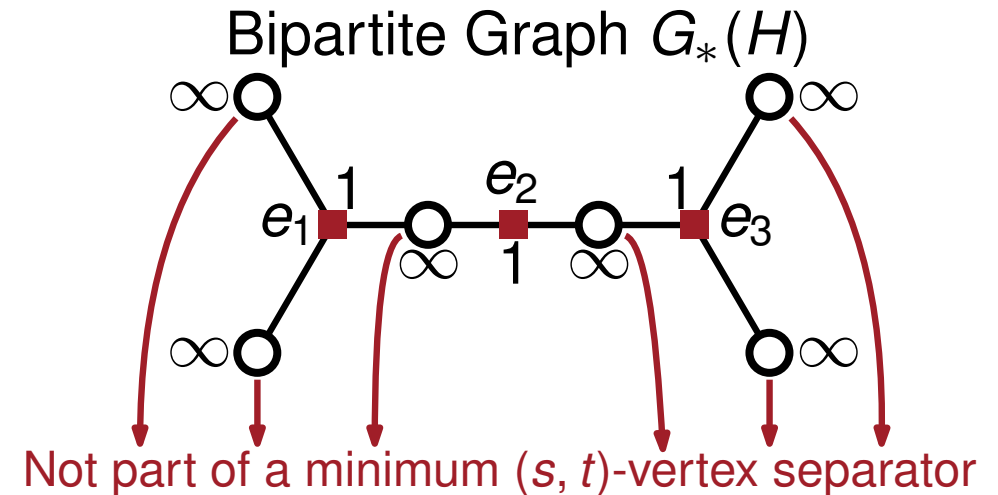
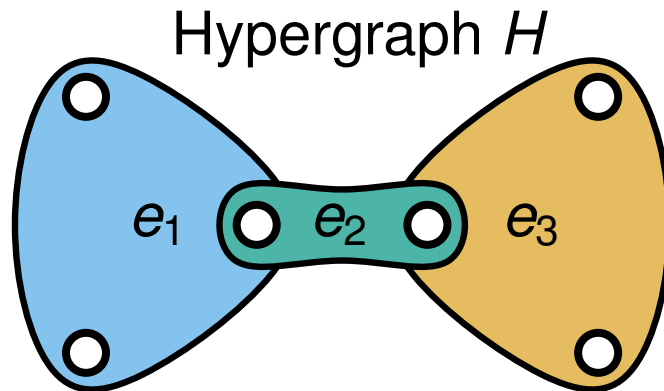
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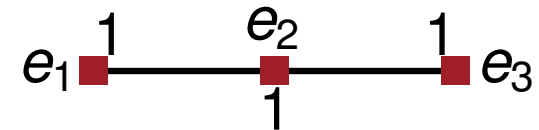
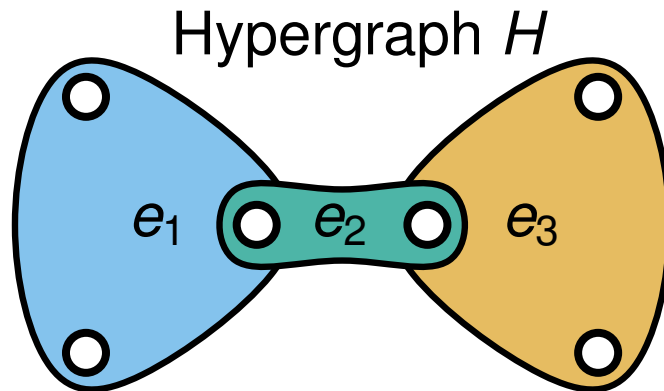
# Hypergraph Flow Network - Low Degree Vertices



# Hypergraph Flow Network - Low Degree Vertices

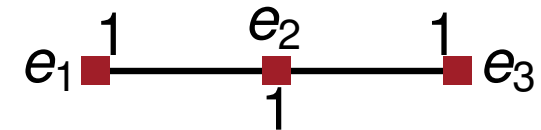
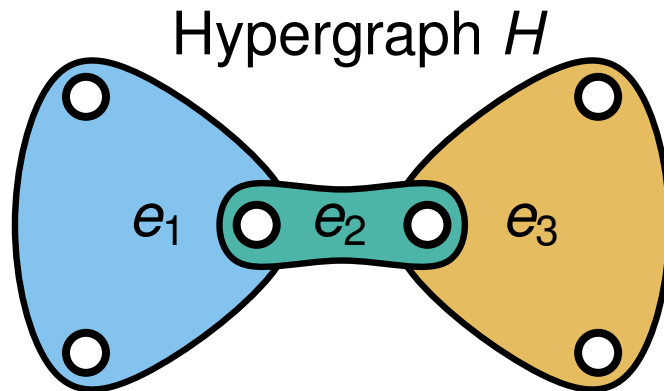


# Hypergraph Flow Network - Low Degree Vertices



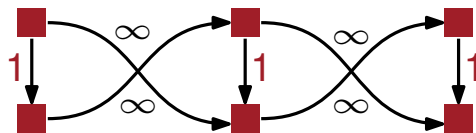
Remove all vertices by adding a clique

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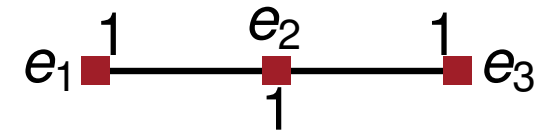
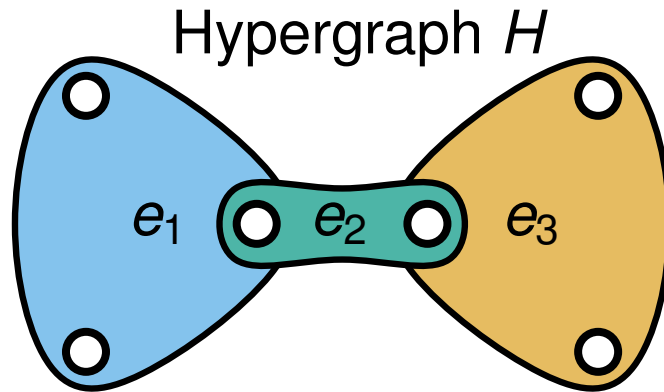


Remove all vertices by adding a clique

Our Network

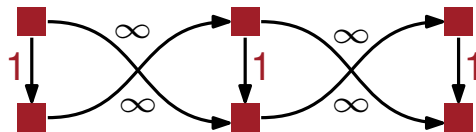


# Hypergraph Flow Network - Low Degree Vertices



Remove all vertices by adding a clique

Our Network



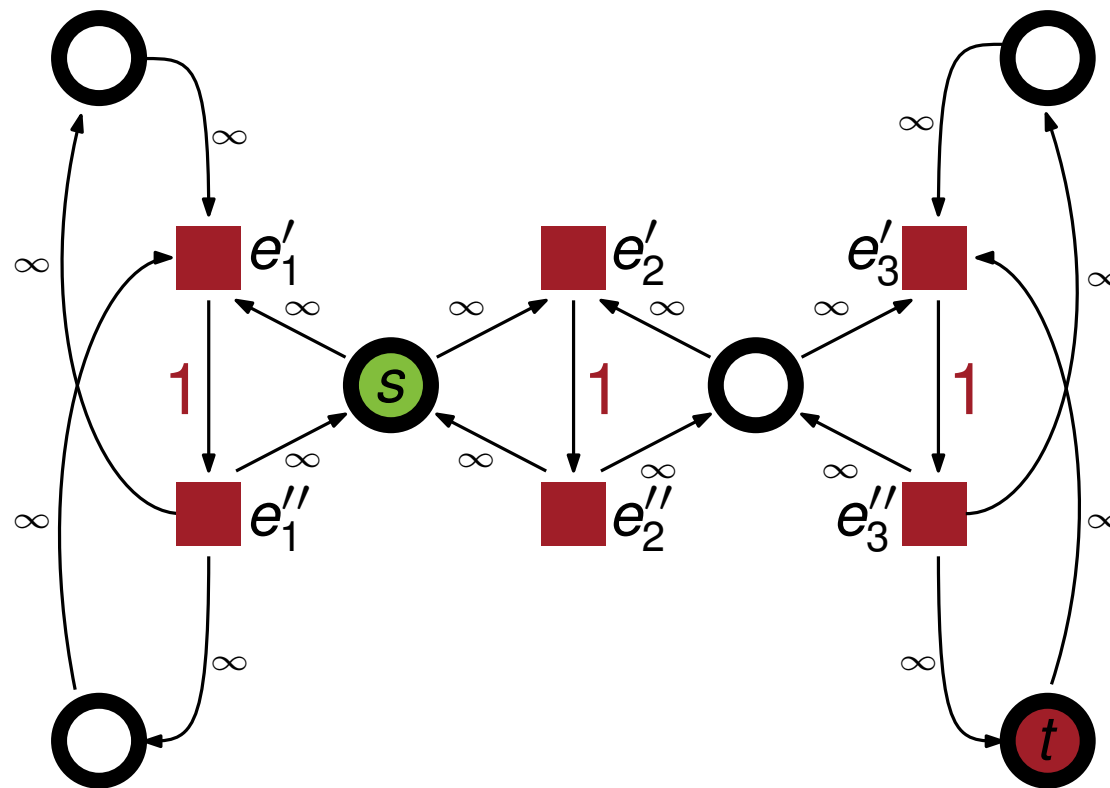
A hypernode  $v$  induces ...

- ...  $2d(v)$  edges in the Lawler Network
- ...  $d(v)(d(v) - 1)$  edges in our network

If  $d(v) \leq 3$ , then  $d(v)(d(v) - 1) \leq 2d(v)$

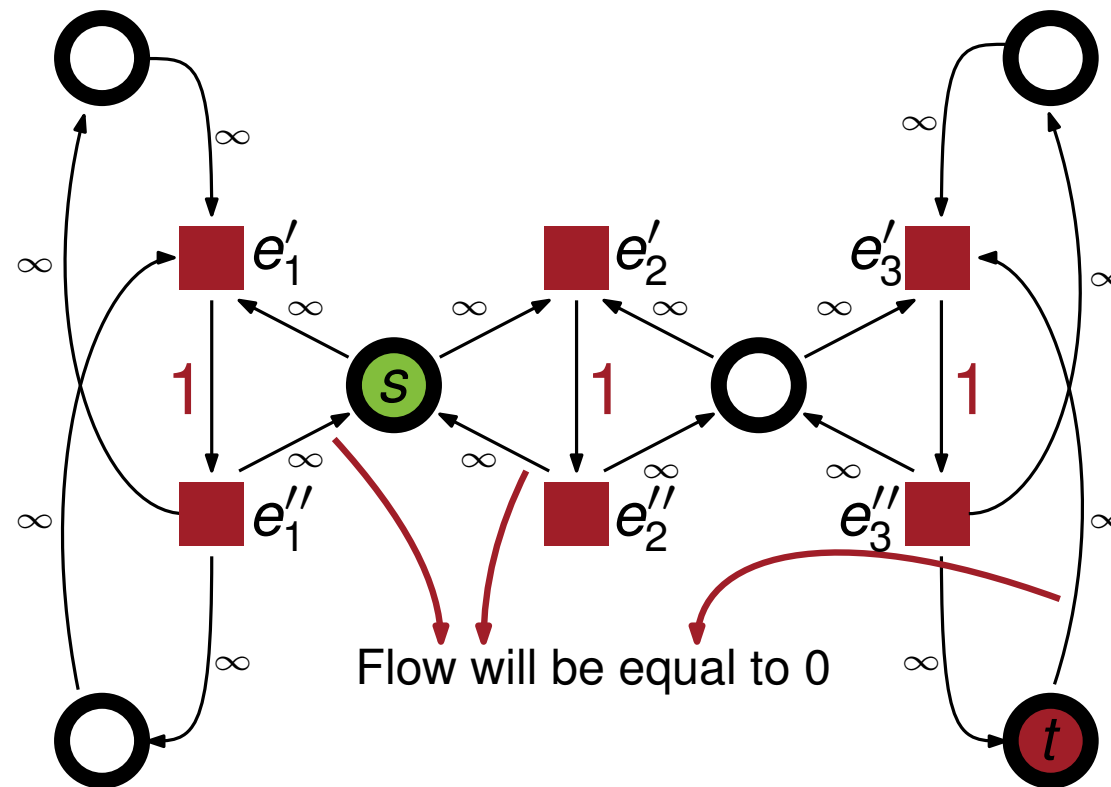


# Removing Source and Sink Vertices



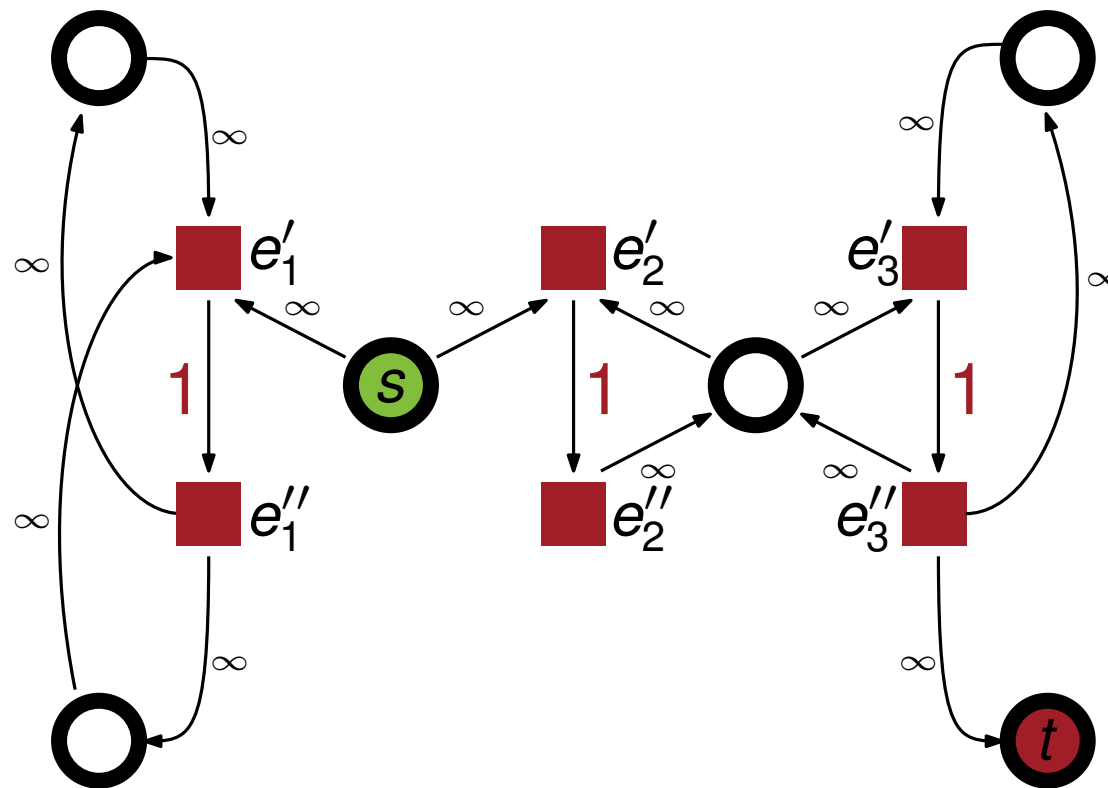
Lawler Network

# Removing Source and Sink Vertices



Lawler Network

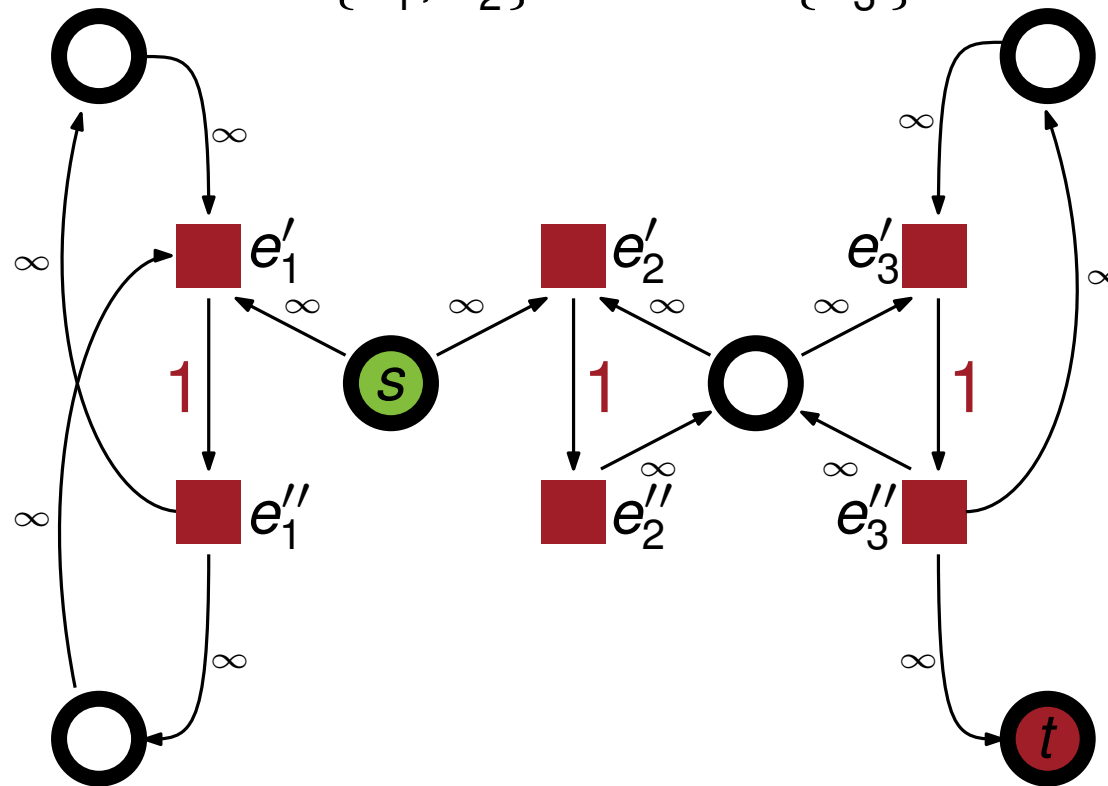
## Removing Source and Sink Vertices



# Lawler Network

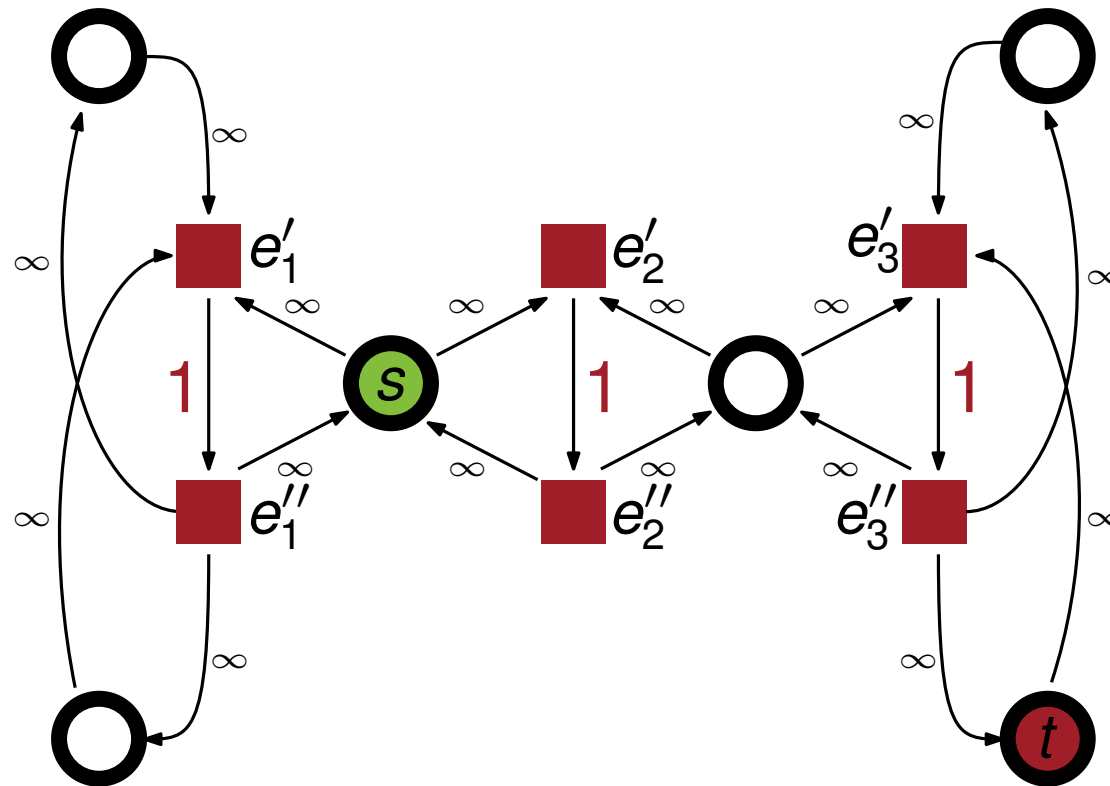
# Removing Source and Sink Vertices

Corresponds to *Multi-Source Multi-Sink* problem with  
 $S = \{e'_1, e'_2\}$  and  $T = \{e''_3\}$

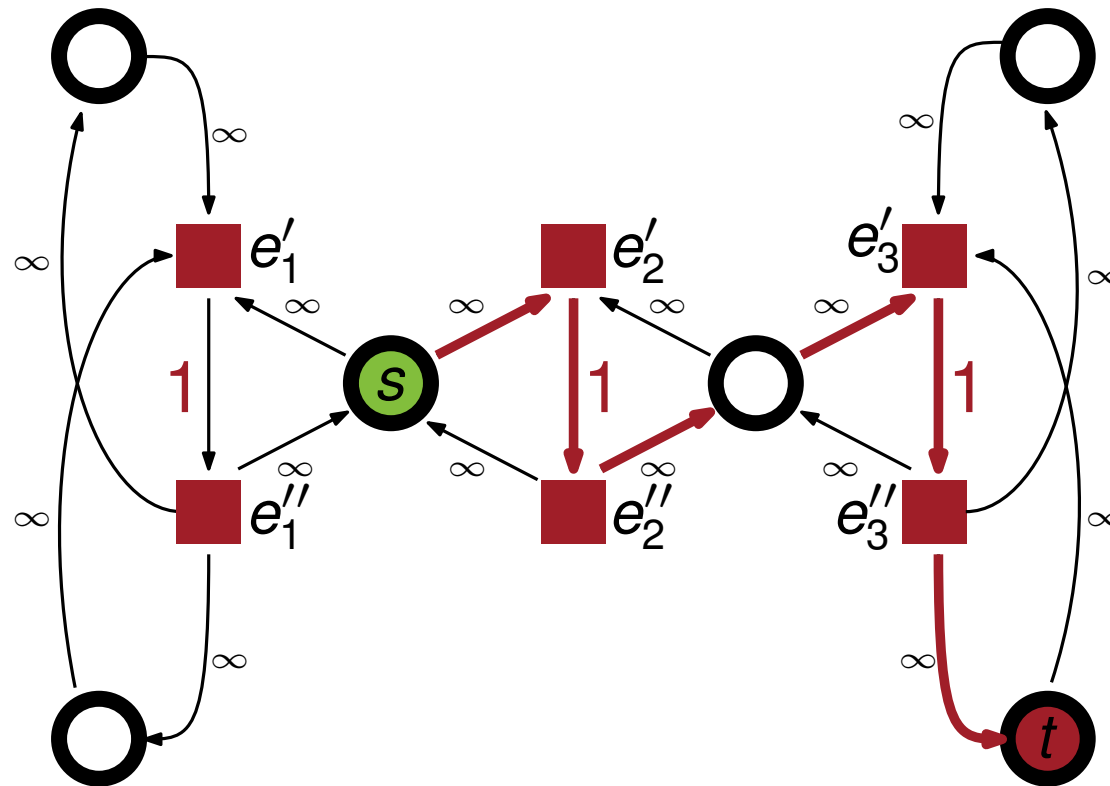


Lawler Network

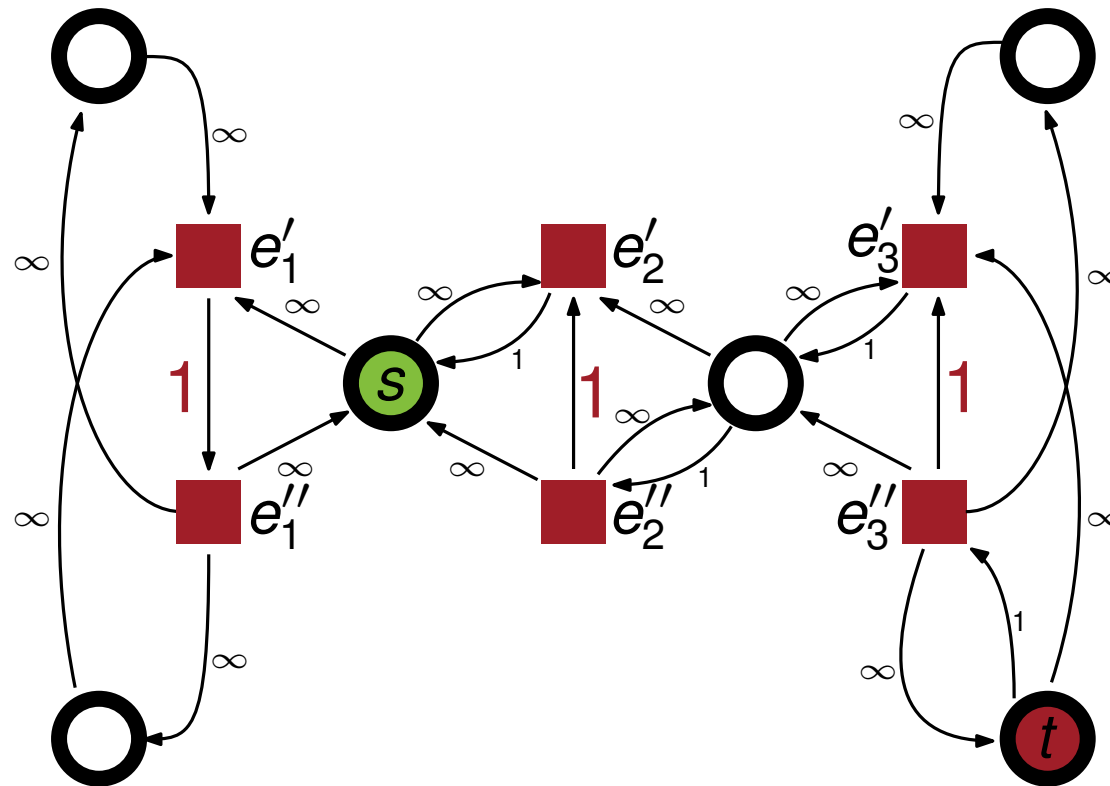
# Reconstruction of Minimum $(s, t)$ -Bipartition



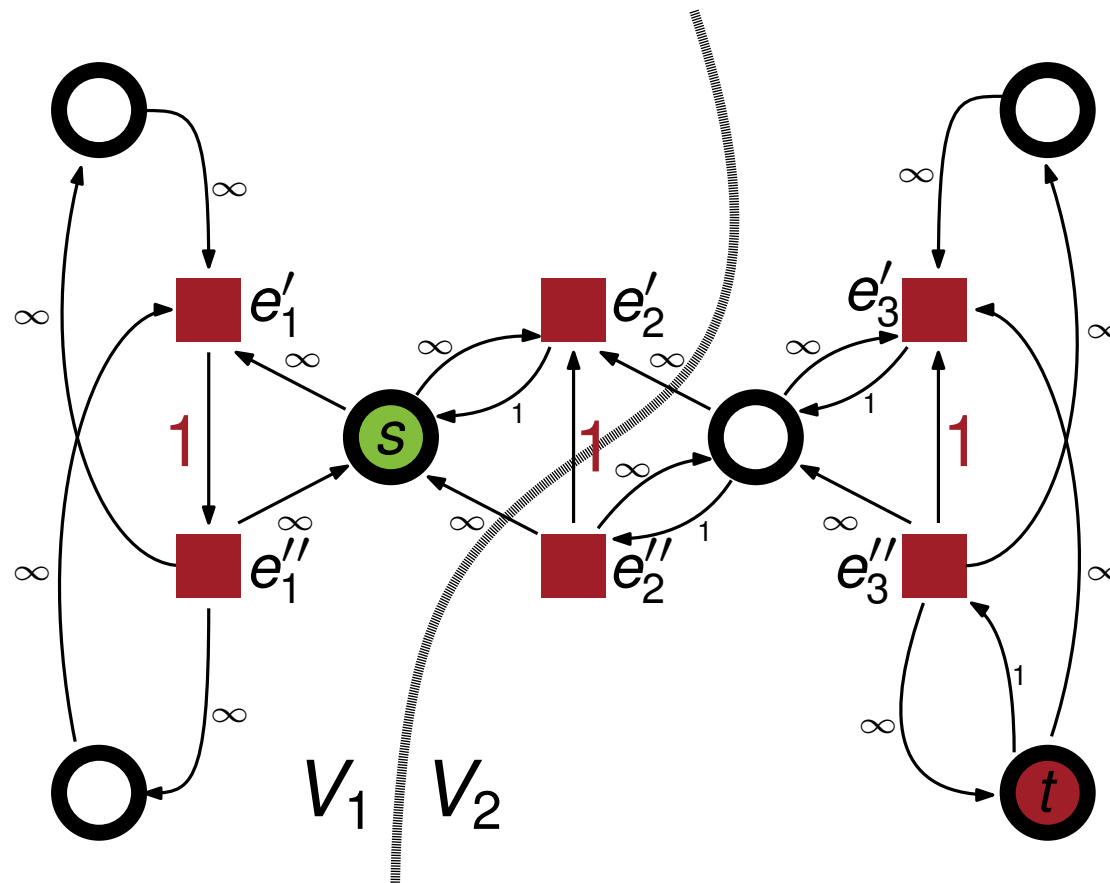
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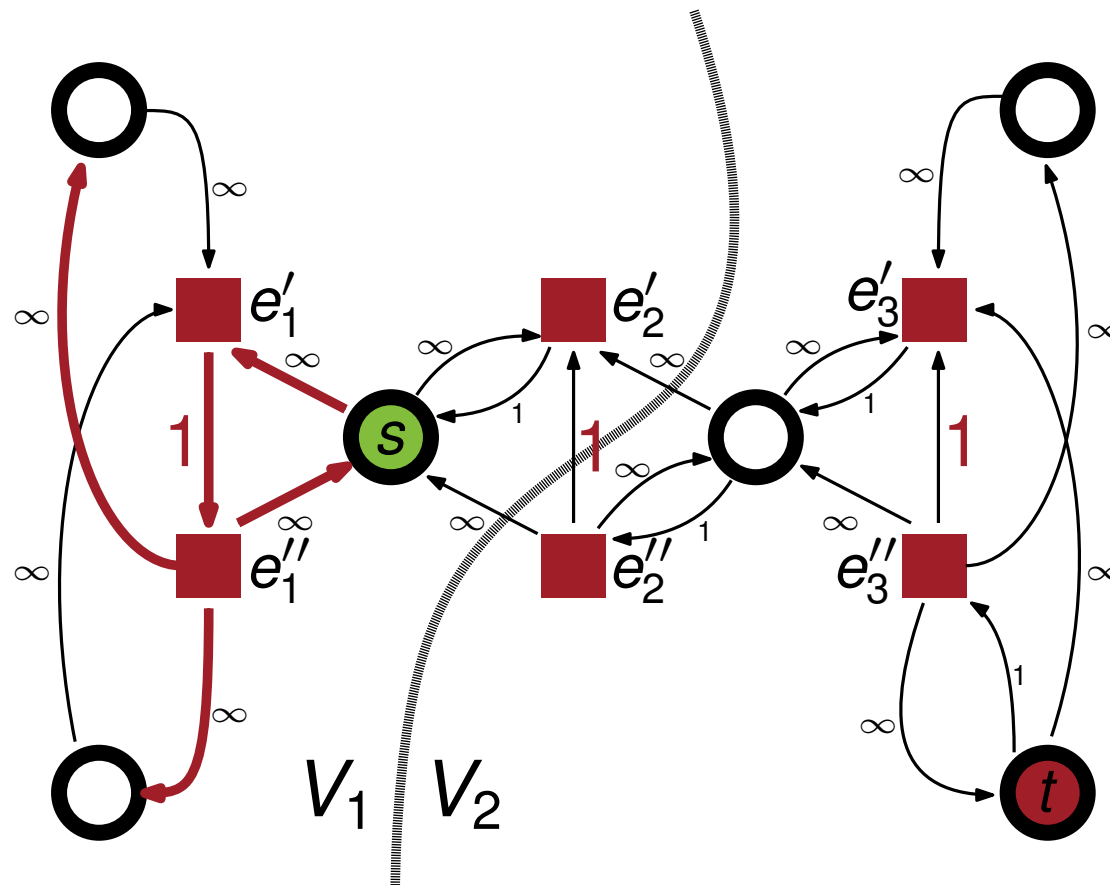


All nodes *reachable* from  $s$  are part of  $V_1$  and  $V_2 = V \setminus V_1$



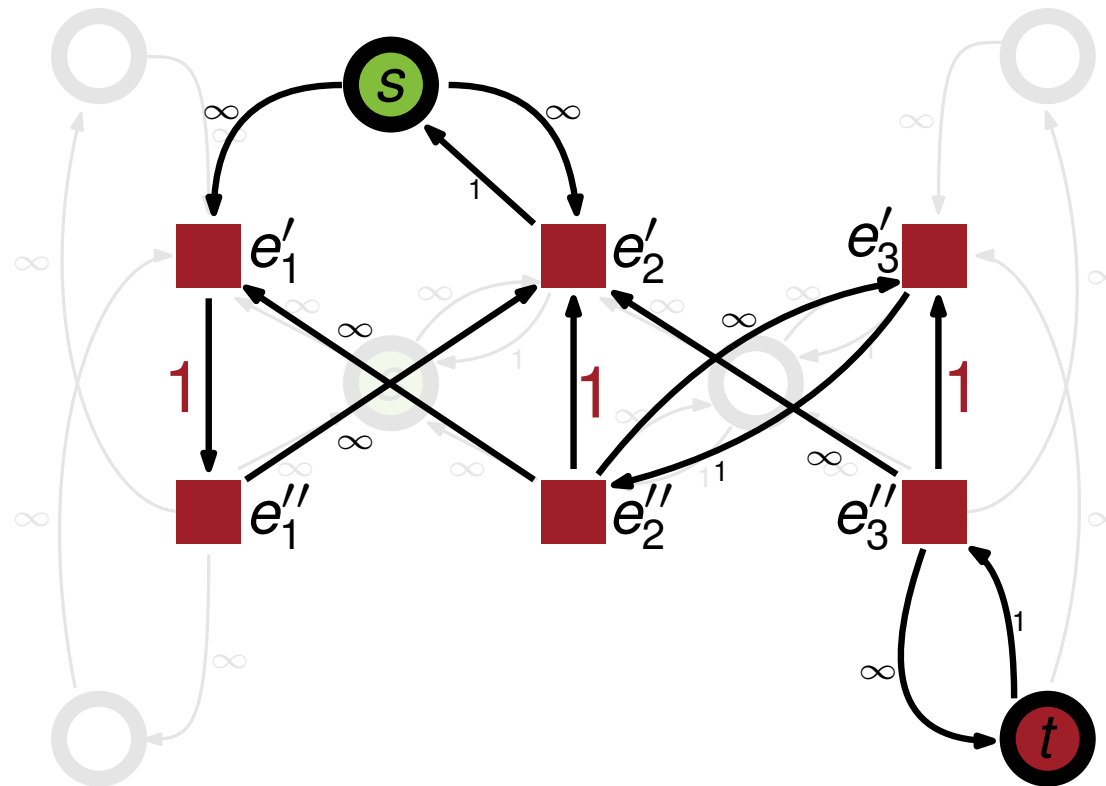
# Reconstruction of Minimum $(s, t)$ -Bipartition

For each hypernode  $v \in V_1$ , there exists at least one  $e \in I(v)$  with  $e'' \in V_1$

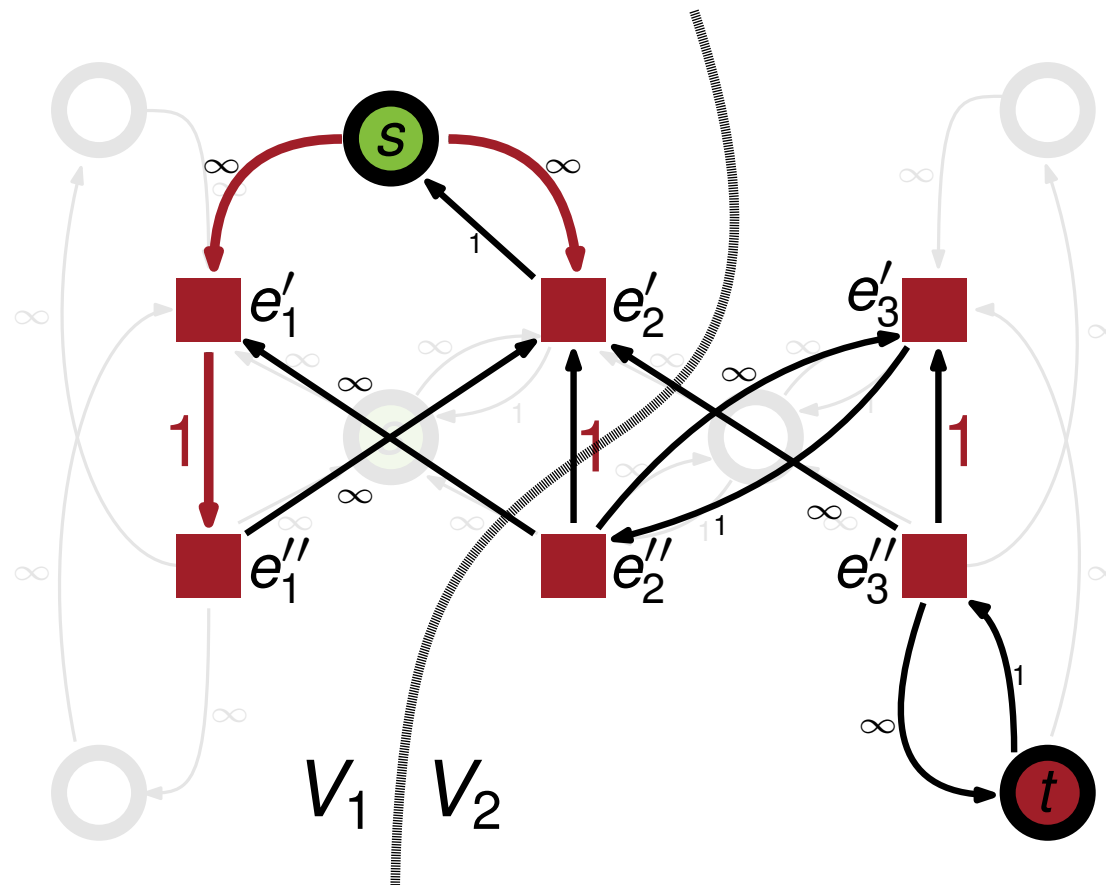


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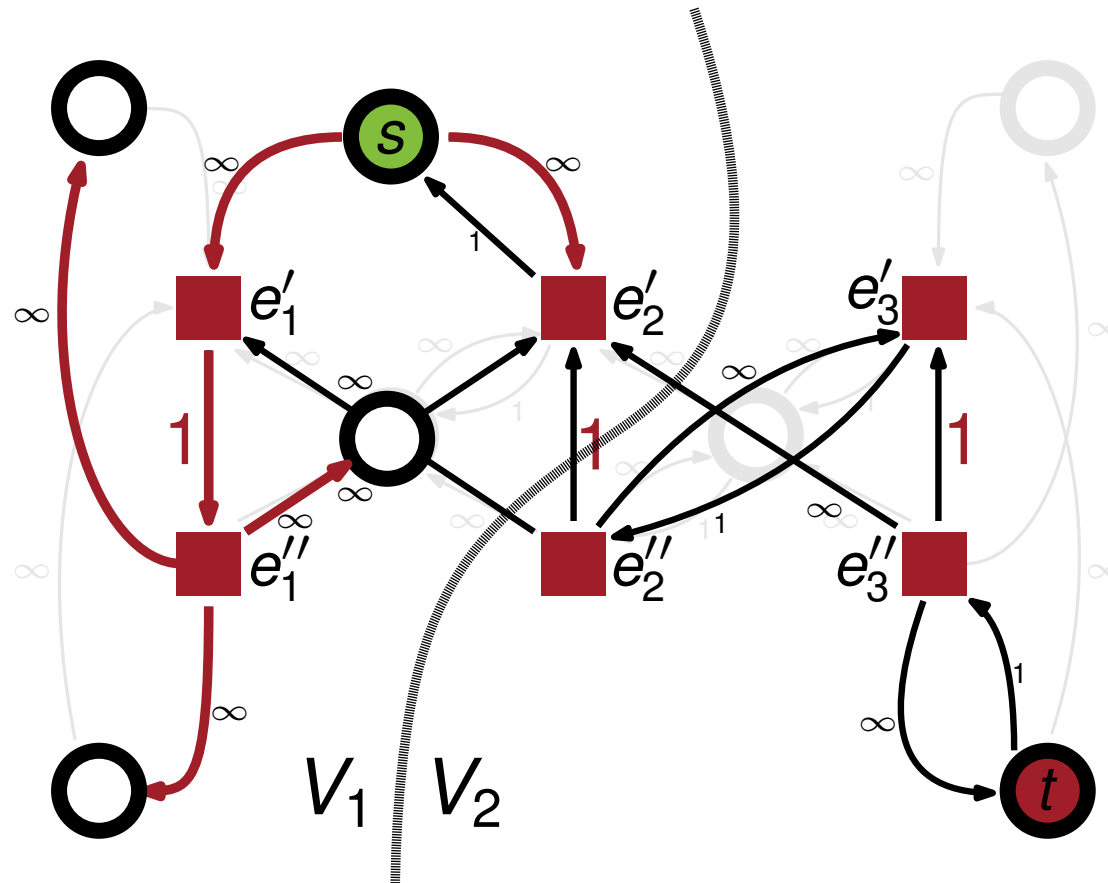
# Reconstruction of Minimum $(s, t)$ -Bipartition



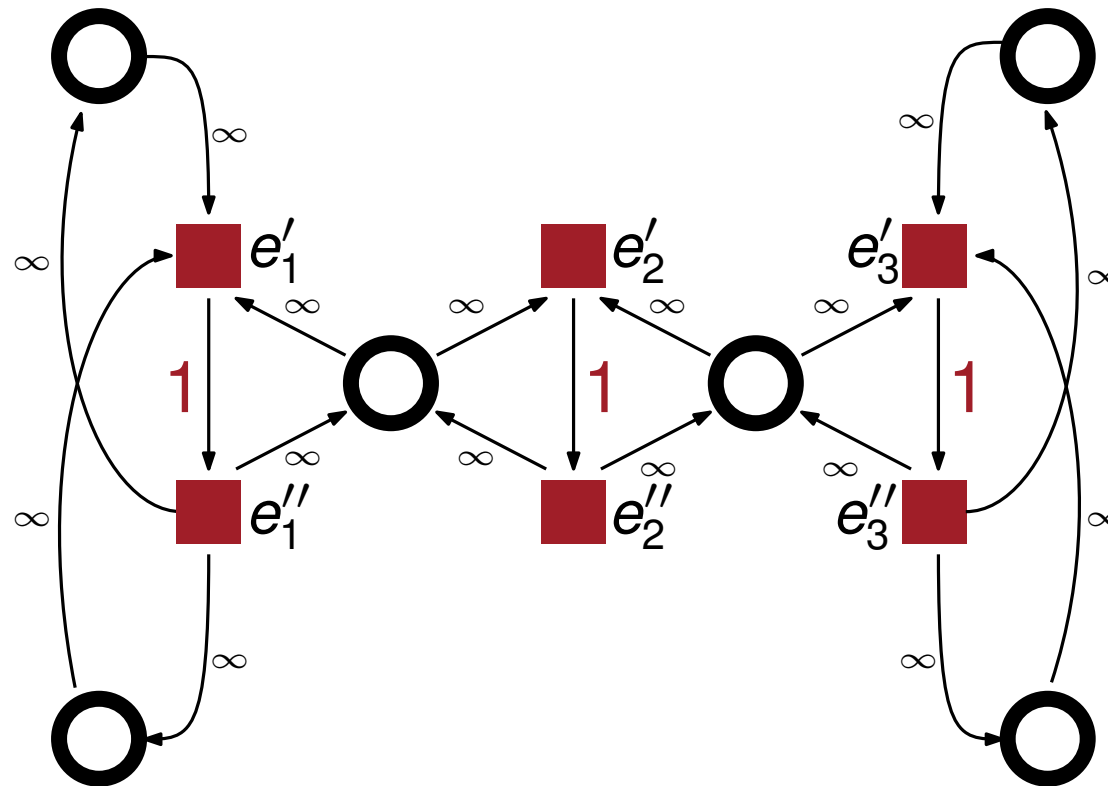
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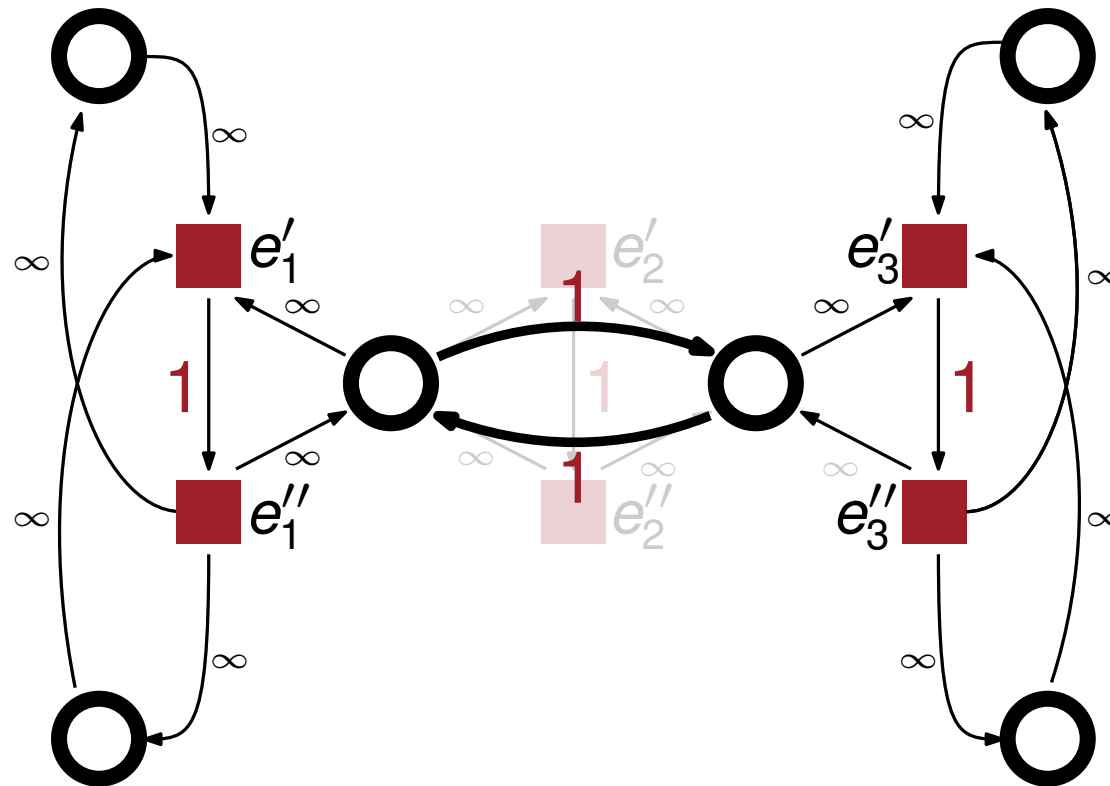


# Hypergraph Flow Network - Summary



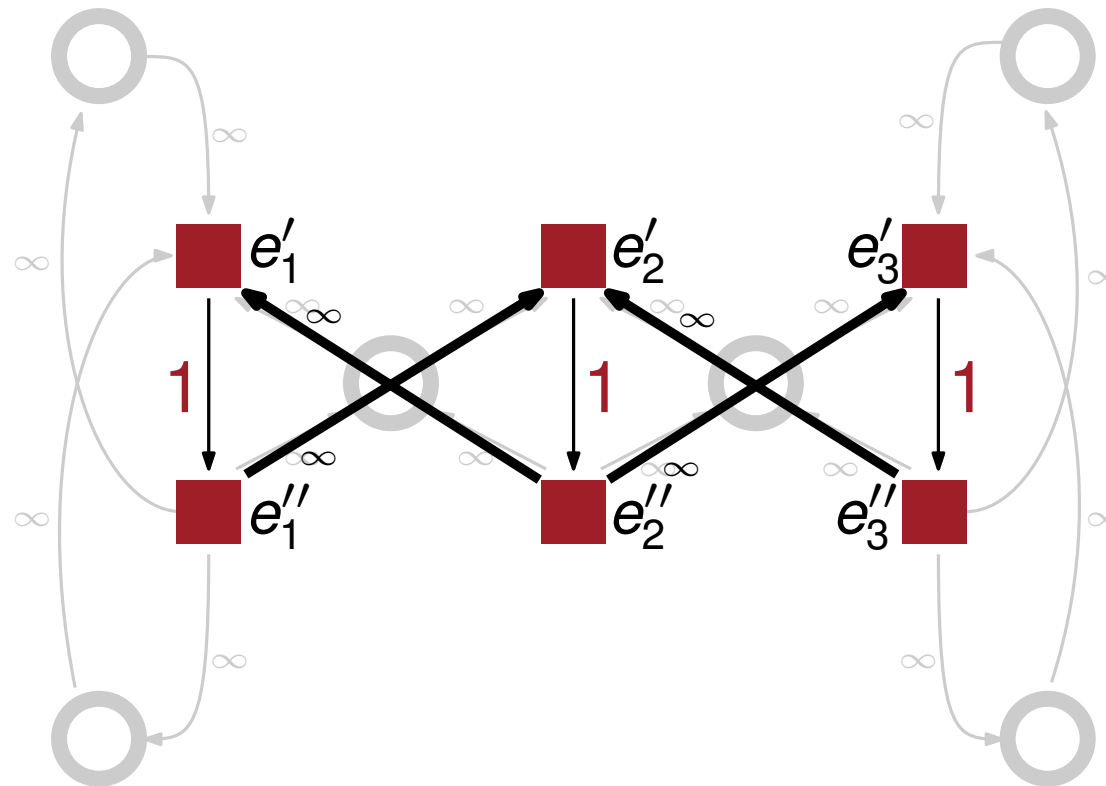
# Lawler Network

# Hypergraph Flow Network - Summary



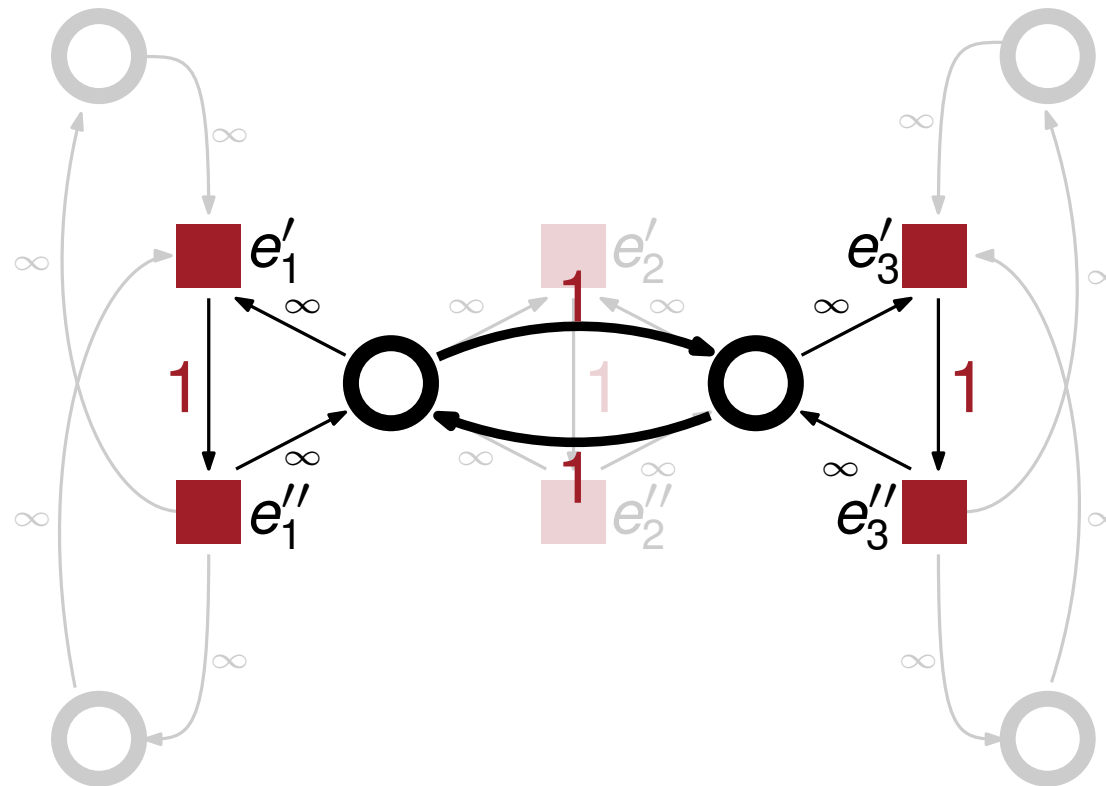
Wong Network

# Hypergraph Flow Network - Summary



Our Network

# Hypergraph Flow Network - Summary

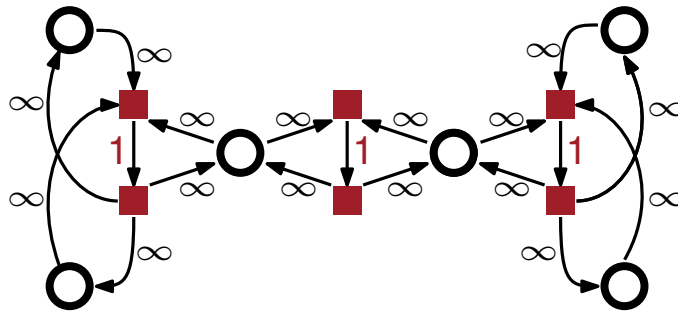


Hybrid Network



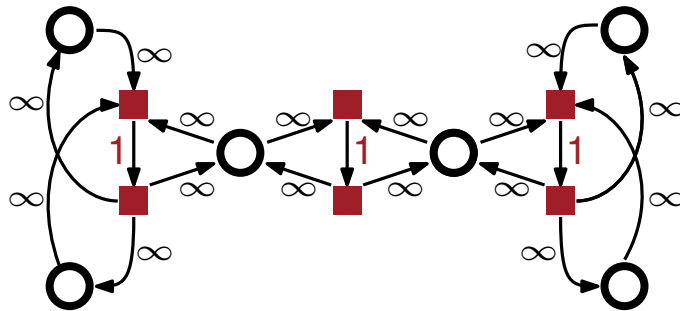
# Hypergraph Flow Network - Summary

Lawler Network

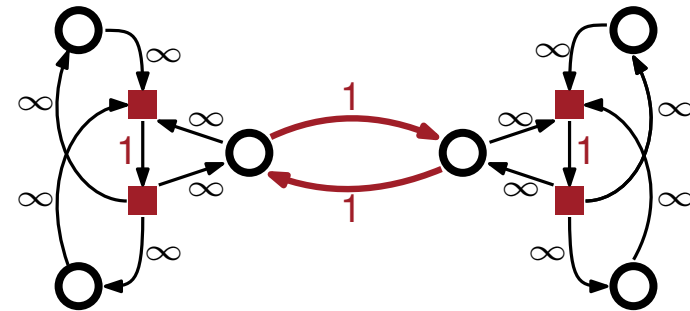


# Hypergraph Flow Network - Summary

Lawler Network

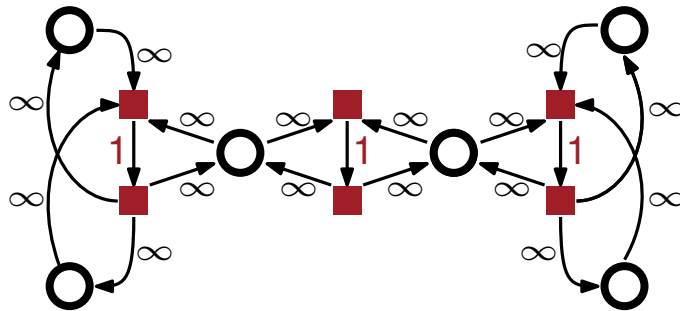


Wong Network

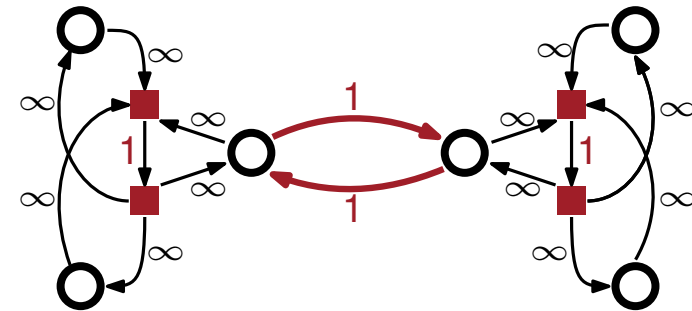


# Hypergraph Flow Network - Summary

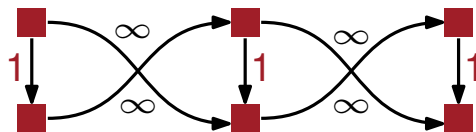
Lawler Network



Wong Network

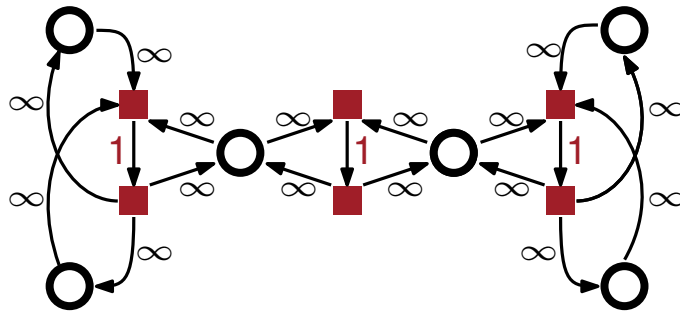


Our Network

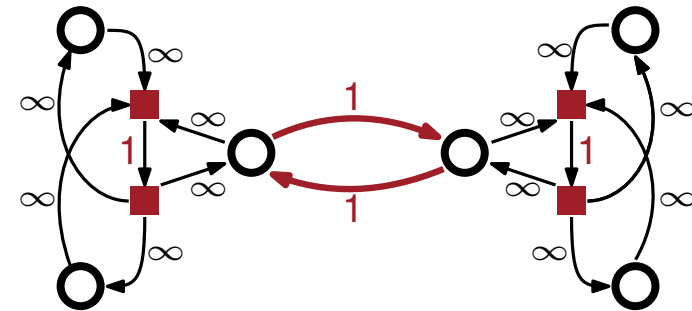


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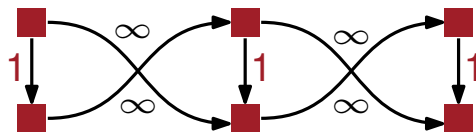
Lawler Network



Wong Network



Our Network



Hybrid Network

