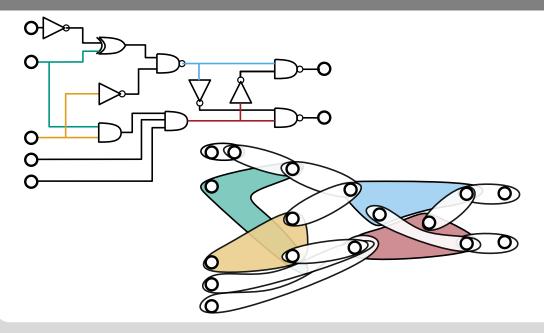


High Quality Hypergraph Partitioning via Max-Flow-Min-Cut Computations

Master Thesis · February 16, 2018 **Tobias Heuer**

Institute of Theoretical Informatics · Algorithmics Group



Outline



Task

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

Outline



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

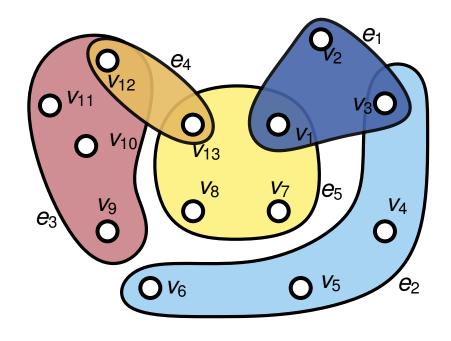
Contributions

- Outperforms 5 different systems on 73% of 3216 benchmark instances
- Improve quality of KaHyPar by 2.5%, while only incurring a slowdon 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
- lacktriangle Hypergraphs \Rightarrow (\mathbf{d} -ary) relationships
- Hypergraph $H = (V, E, c, \omega)$
 - Vertex set $V = \{1, ..., n\}$
 - Edge set $E \subseteq \mathcal{P}(V) \setminus \emptyset$
 - Node weights $c: V \to \mathbb{R}_{\geq 1}$
 - Edge weights $\omega: E \to \mathbb{R}_{>1}$

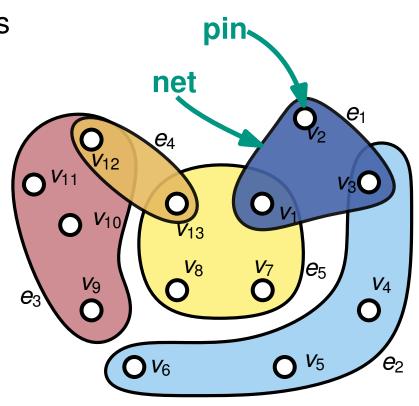


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$$|P| = \sum_{e \in E} |e| = \sum_{v \in V} d(v)$$



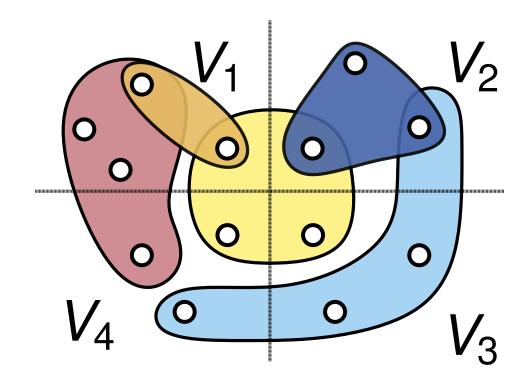


[from SEA'17]

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

lacksim blocks V_i are roughly equal-sized:

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



Karlsruhe Institute of Technology

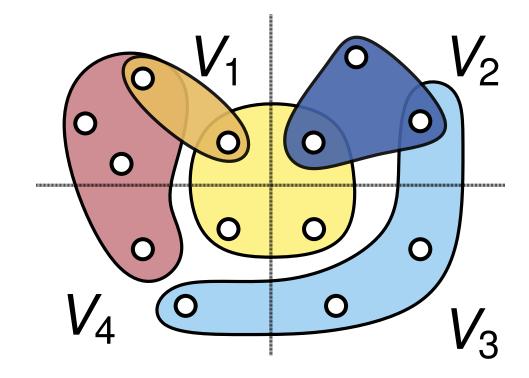
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imbalance parameter





[from SEA'17]

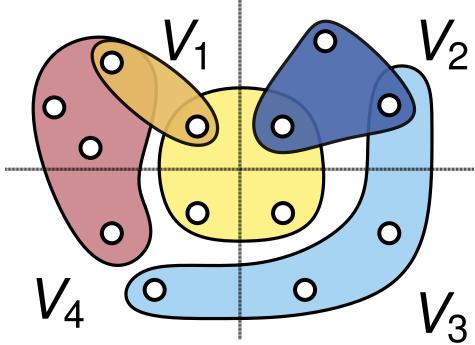
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connectivity objective is minimized:





[from SEA'17]

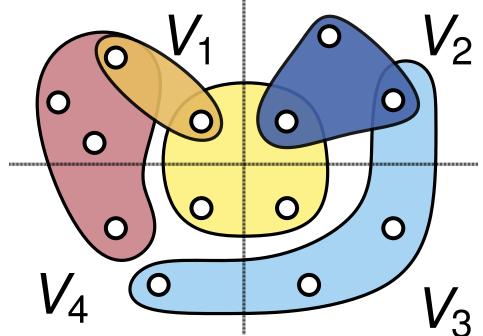
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$$\sum_{e \in \text{cut}} (\lambda - 1) \, \omega(e)$$
connectivity:
blocks connected by net e





[from SEA'17]

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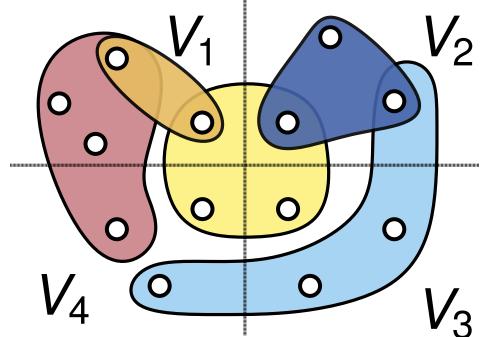
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imbalance parameter

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

connectivity objective is minimized:

$$\sum_{e \in \text{cut}} (\lambda - 1) \, \omega(e) = 6$$
connectivity:
blocks connected by net e

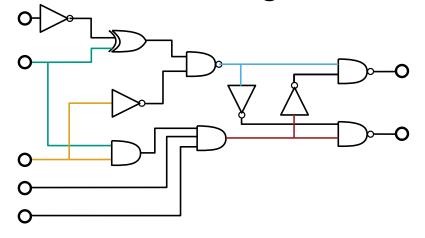


Applications

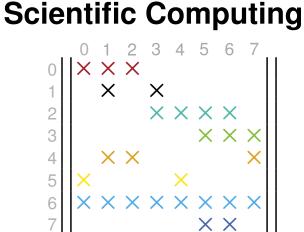
[from SEA'17]

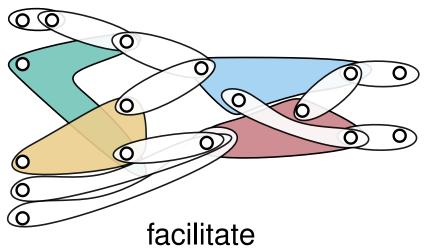


VLSI Design



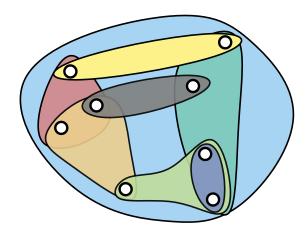
Application Domain





floorplanning & placement

Hypergraph Model



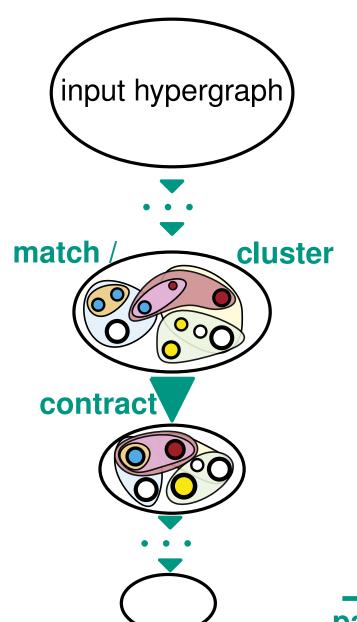
minimize communication

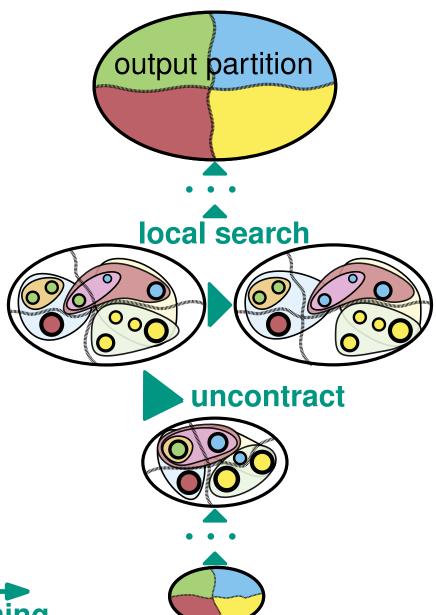
Goal

The Multilevel Framework

[from SEA'17]







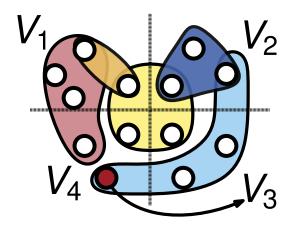


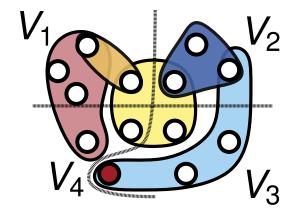


FM Algorithm



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



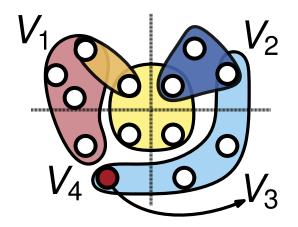


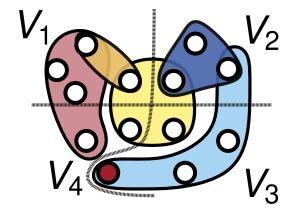
Moving lacktriangle from V_4 to V_3 reduces cut by 1

FM Algorithm



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



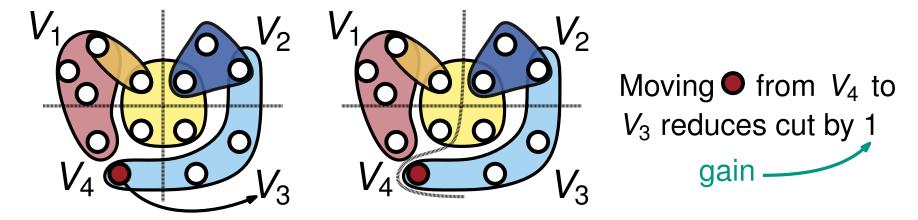


Moving lacktriangle from V_4 to V_3 reduces cut by 1 gain

FM Algorithm



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

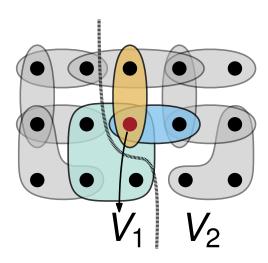


- Performs moves of vertices with maximum gain in each step
- All modern hypergraph partitioners implements variations of the FM algorithm

FM Algorithm - Disadvantages



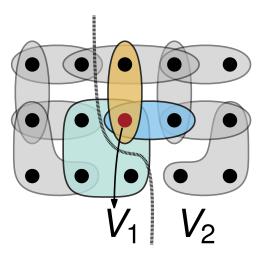
- Only incorparates local informations about the problem structure
 - Heavily depends on initial partition
 - In multilevel context: Depends on quality of coarsening



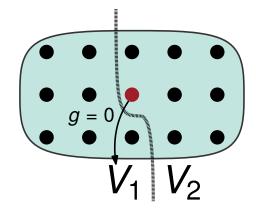
FM Algorithm - Disadvantages



- Only incorparates 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





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

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



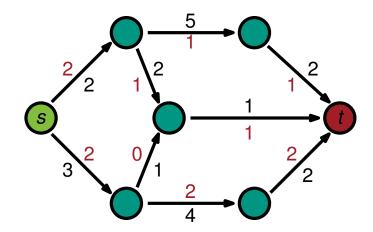
Given a graph G = (V, E, u) and two nodes $s, t \in V$

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

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

- $\forall (v, w) \in E : f(v, w) \leq u(v, w)$

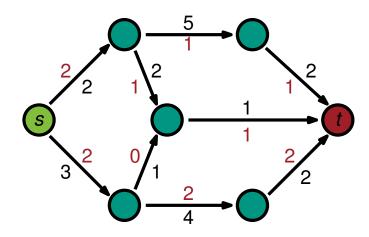
The value of the flow is $|f| = \sum_{(s,v) \in E} f(s,v)$





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

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

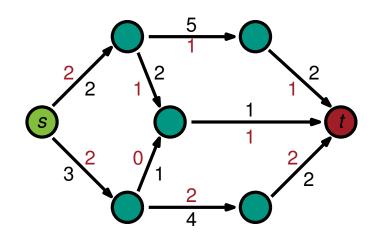


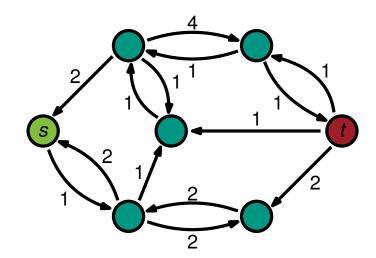


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The **residual graph** $G_f = (V, E_f, r_f)$ contains all edges $(v, w) \in V \times V$ with $r_f(v, w) > 0$





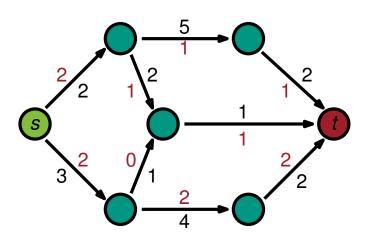


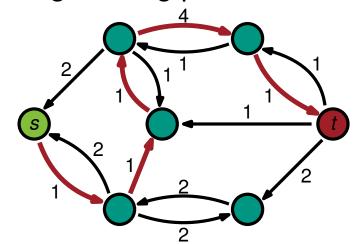
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- An augmenting path is a path in G_t from s to t
- \blacksquare f is a **maximum flow**, if there is no augmenting path from s to t in G_f

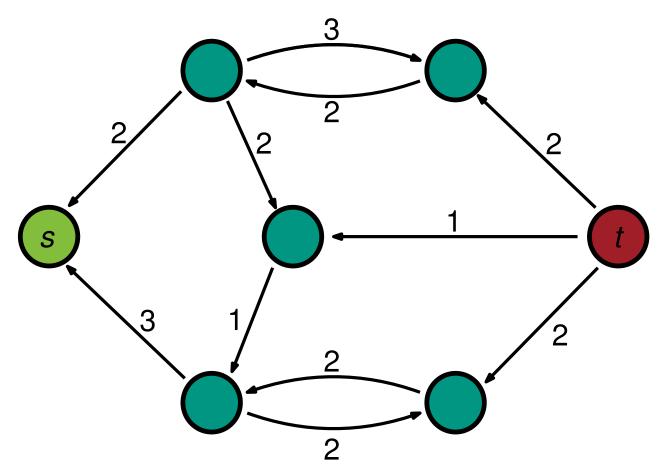




Minimum (s, t)-Bipartition



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

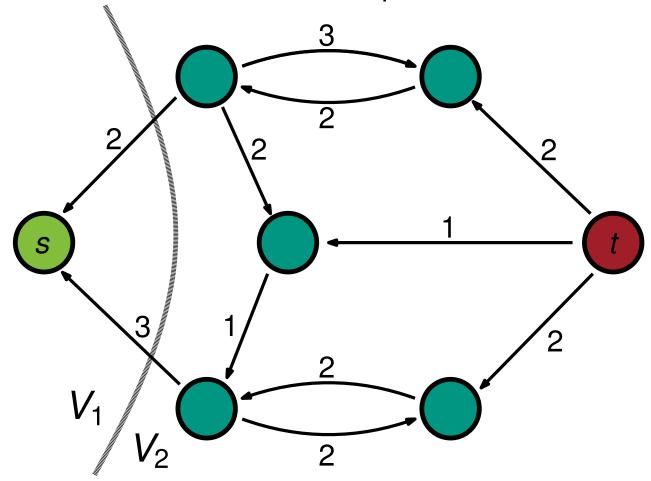


Residual Graph G_f of a maximum flow f

Minimum (s, t)-Bipartition



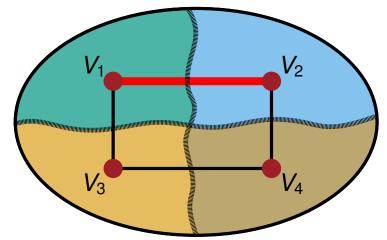
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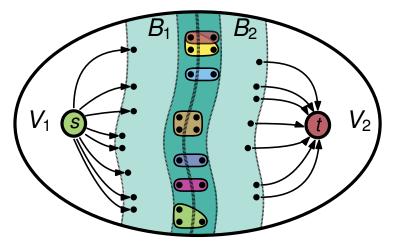
Residual Graph G_f of a maximum flow f

Our Flow-Based Refinement Framework

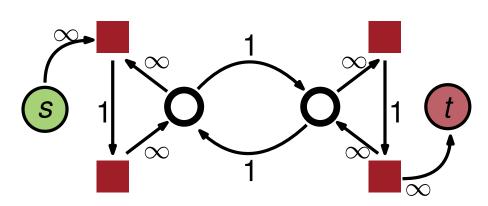




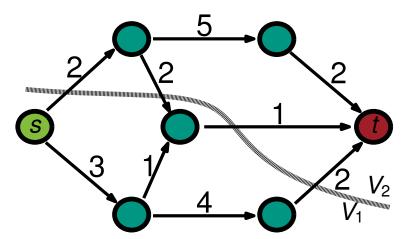
Select two adjacent blocks for refinement



Build Flow Problem



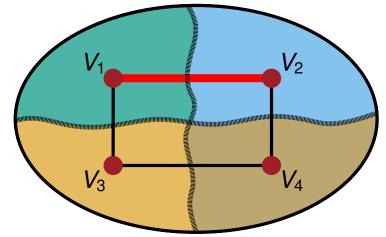
Solve Flow Problem



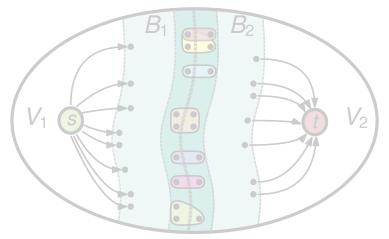
Find feasible minimum cut

Our Flow-Based Refinement Framework

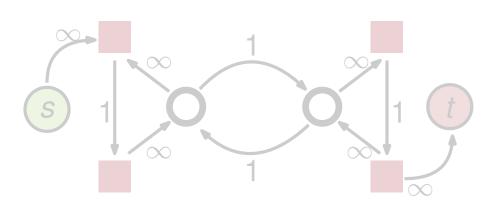




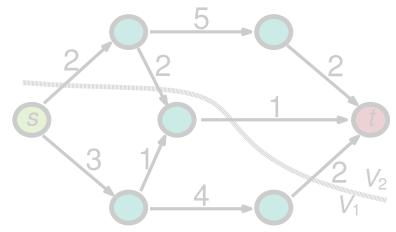
Select two adjacent blocks for refinement



Build Flow Problem

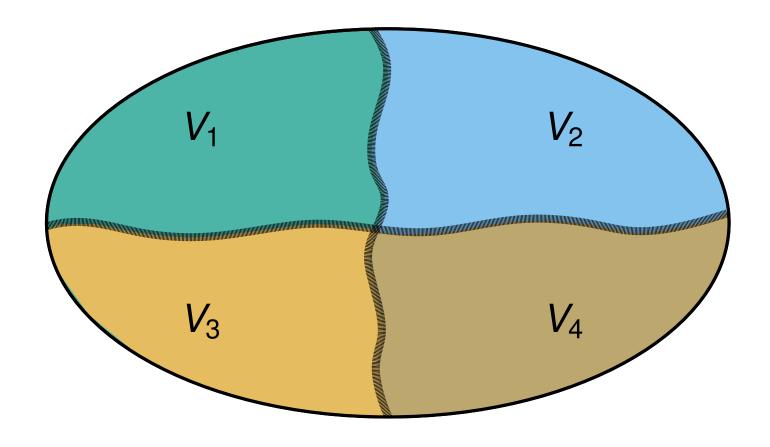


Solve Flow Problem

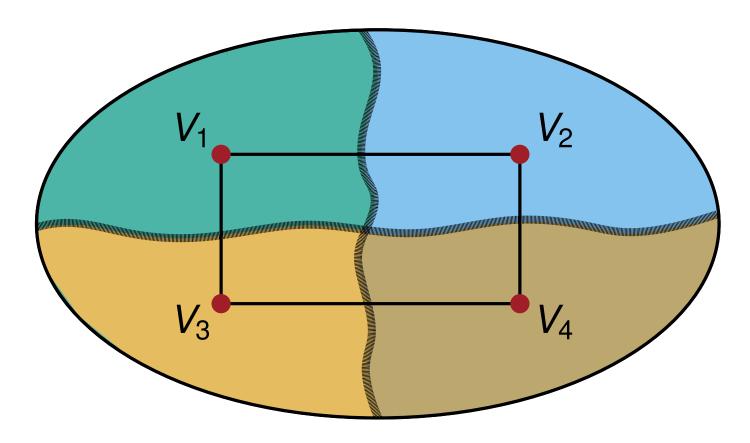


Find feasible minimum cut









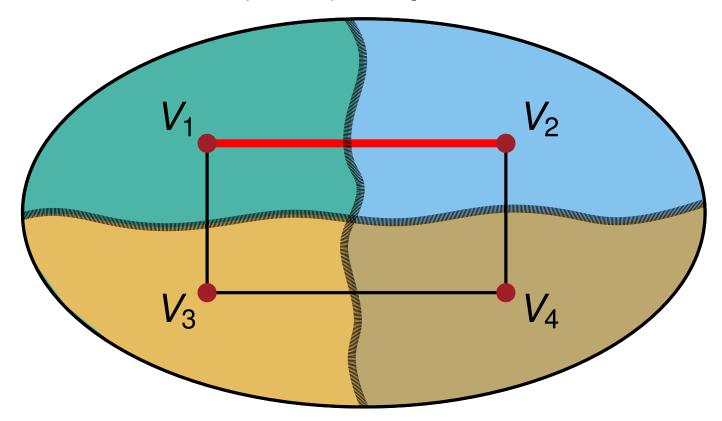
Build Quotient Graph





Round 1

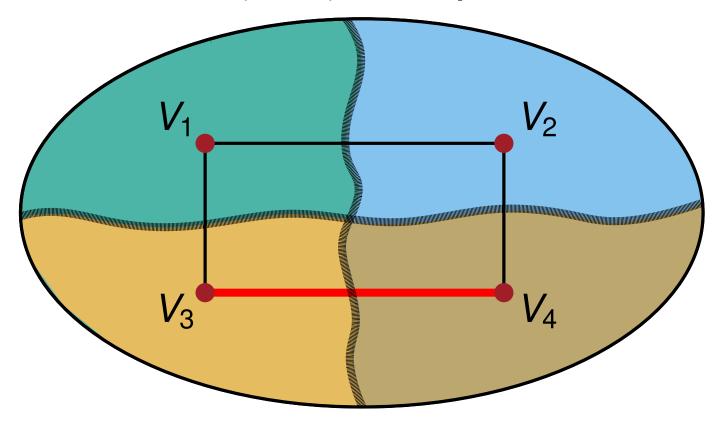
 $refine(V_1, V_2) = Improvement!$





Round 1

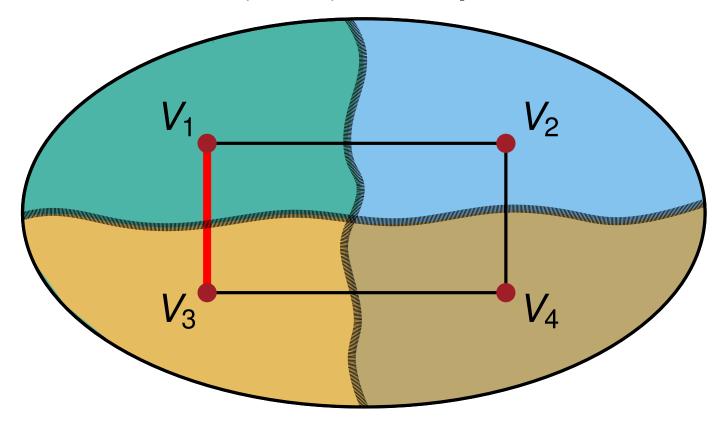
 $refine(V_3, V_4) = No Improvement!$





Round 1

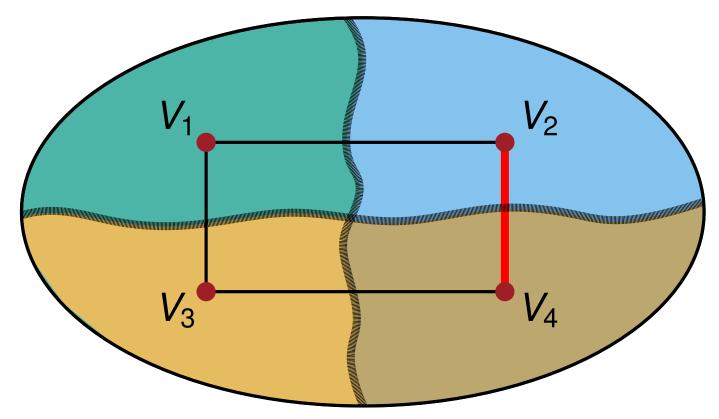
 $refine(V_1, V_3) = No Improvement!$





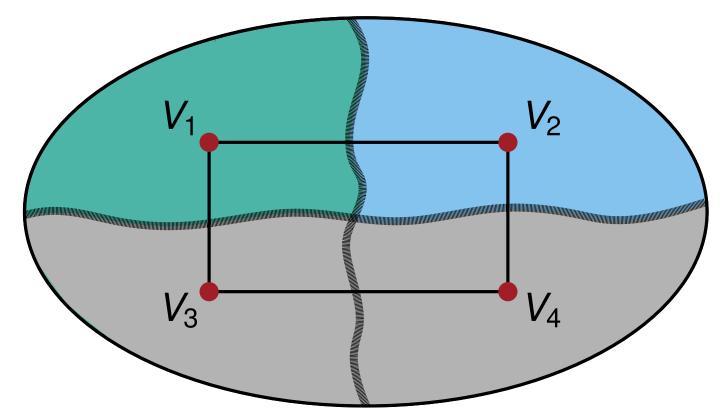
Round 1

 $refine(V_2, V_4) = No Improvement!$





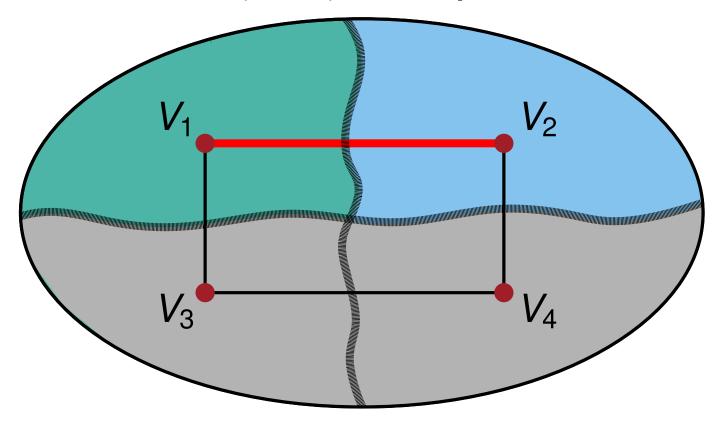
Round 1 Boundary did not change ⇒ Mark block as **inactive**





Round 2

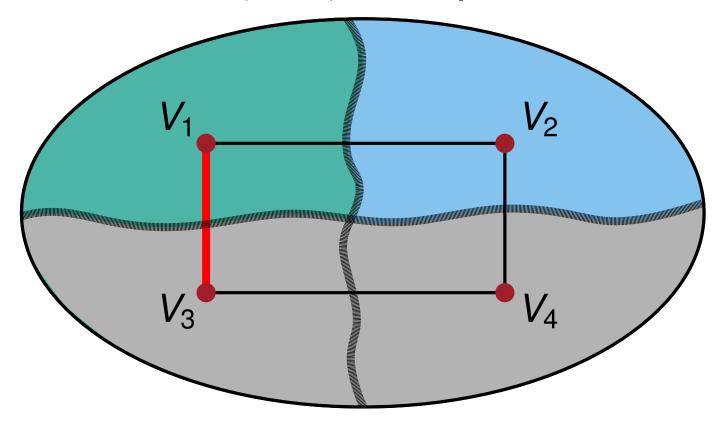
 $refine(V_1, V_2) = No Improvement!$





Round 2

 $refine(V_1, V_3) = No Improvement!$

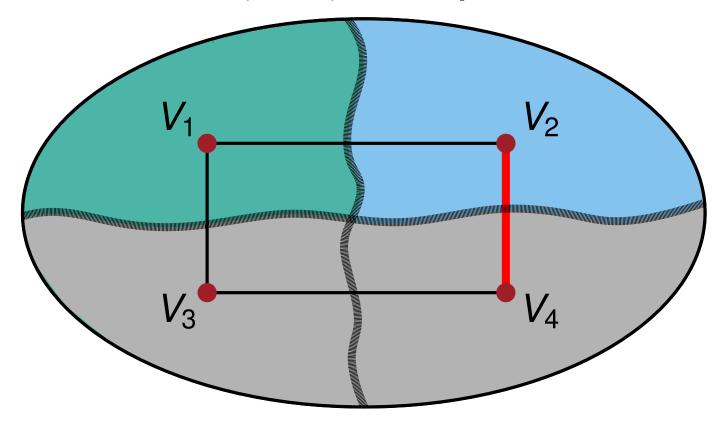


Active Block Scheduling



Round 2

 $refine(V_2, V_4) = No Improvement!$

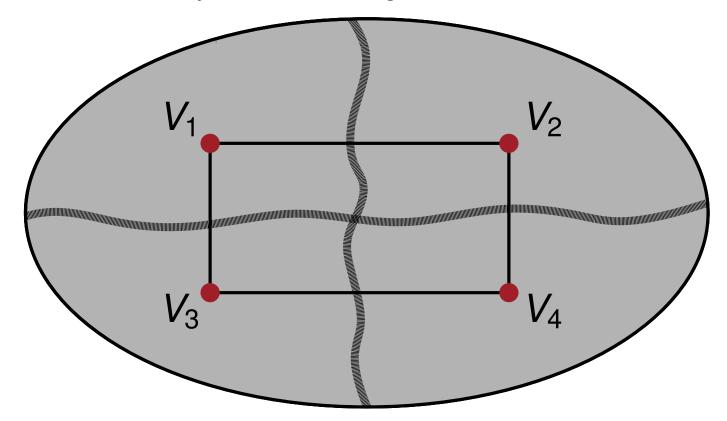


Using 2-way refinement algorithm for active blocks of the quotient graph

Active Block Scheduling



Round 2 Boundary did not change ⇒ Mark block as **inactive**

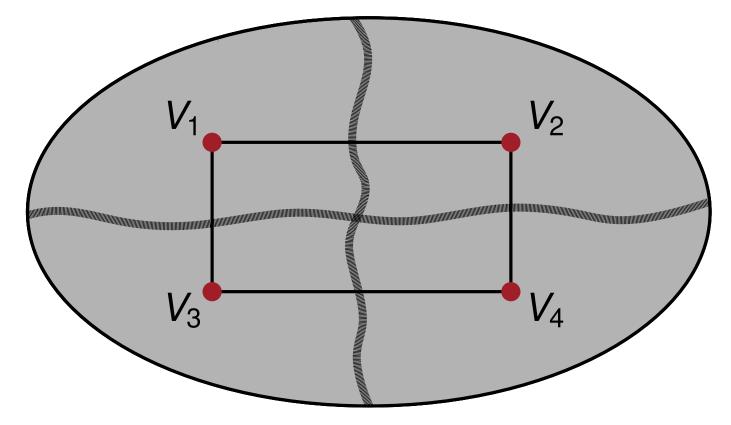


Using 2-way refinement algorithm for active blocks of the quotient graph

Active Block Scheduling



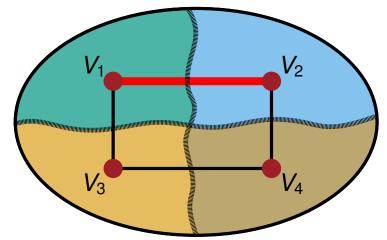
Round 2 All blocks are **inactive** ⇒ Algorithm terminates



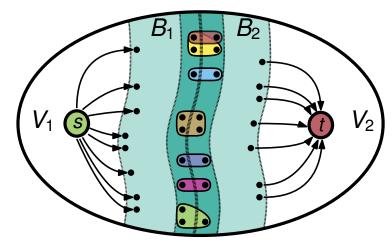
Using 2-way refinement algorithm for active blocks of the quotient graph

Our Flow-Based Refinement Framework

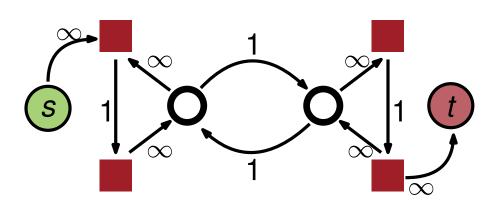




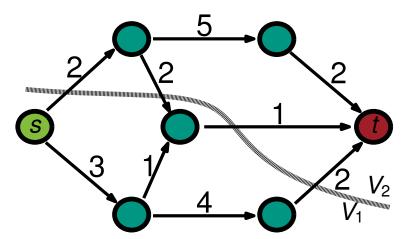
Select two adjacent blocks for refinement



Build Flow Problem



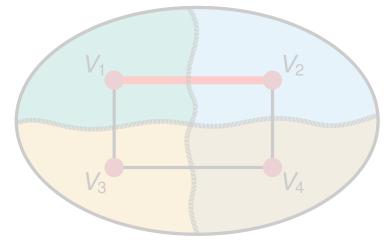
Solve Flow Problem



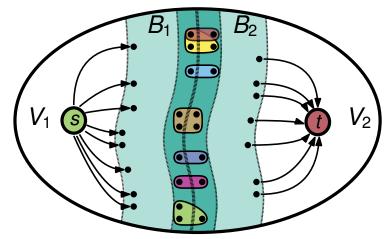
Find feasible minimum cut

Our Flow-Based Refinement Framework

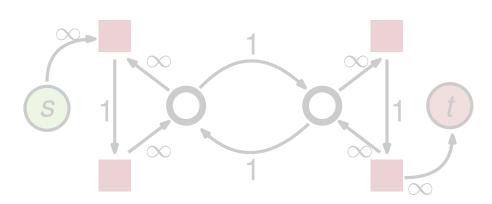




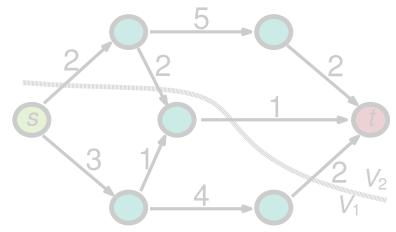
Select two adjacent blocks for refinement



Build Flow Problem

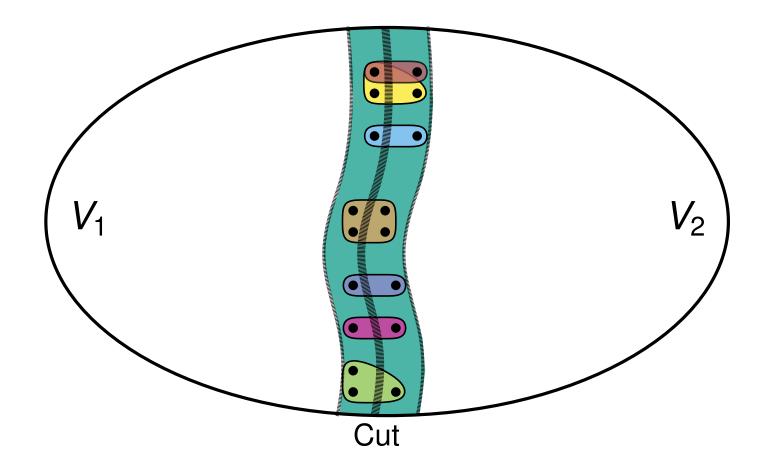


Solve Flow Problem

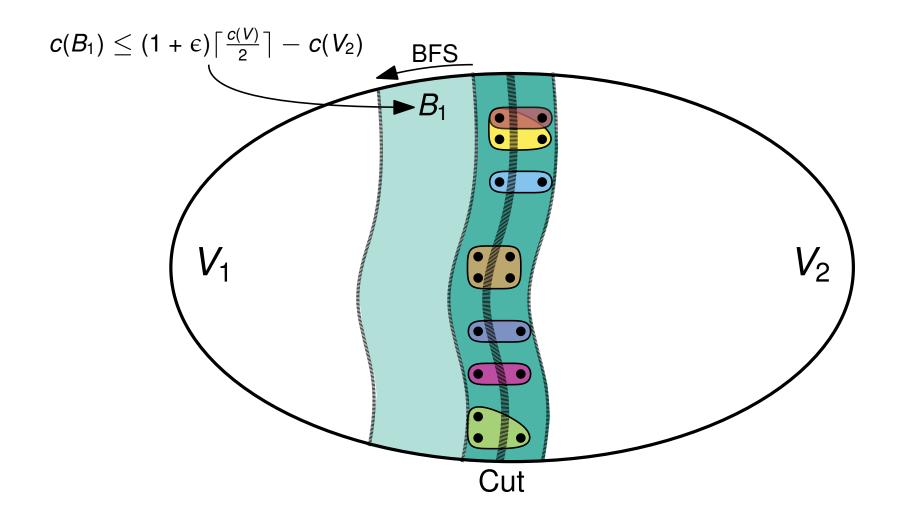


Find feasible minimum cut

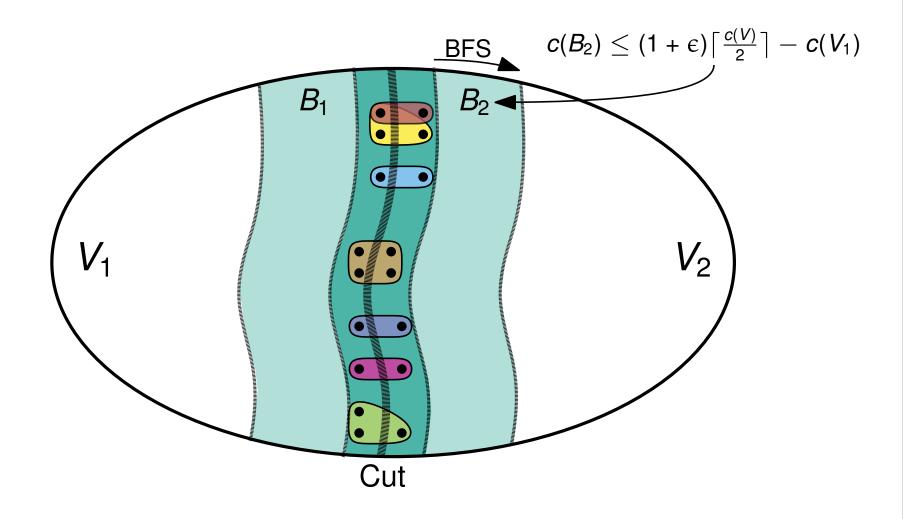




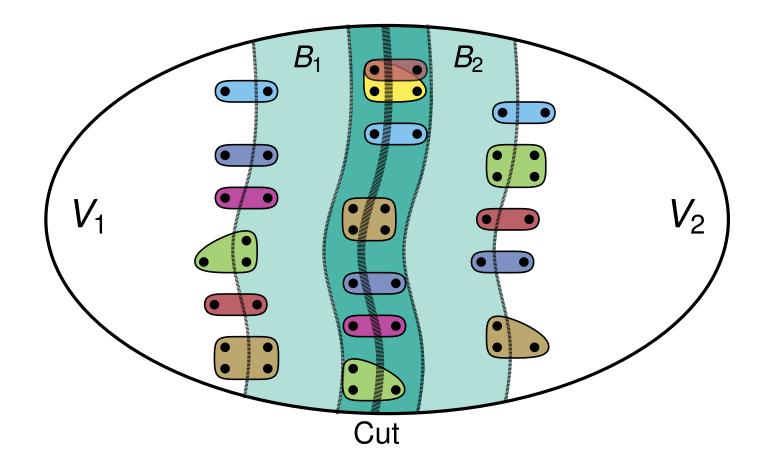




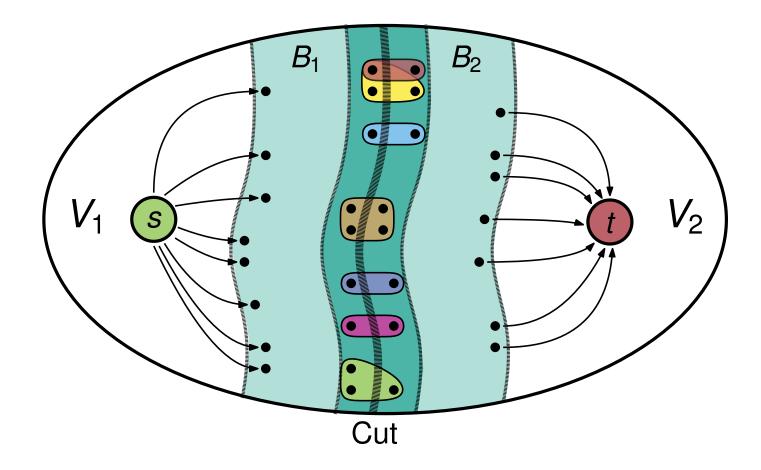














Use $\epsilon' = \alpha \epsilon$ instead of ϵ $c(B_1) \leq (1 + \epsilon') \lceil \frac{c(V)}{2} \rceil - c(V_2)$ $c(B_2) \leq (1 + \epsilon') \lceil \frac{c(V)}{2} \rceil - c(V_1)$ B_1 Cut



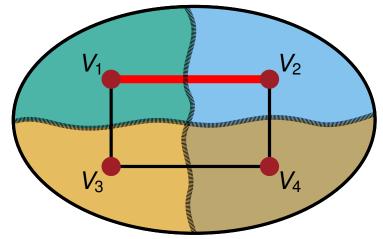
Use $\epsilon' = \alpha \epsilon$ instead of ϵ

If improvement, $\alpha = \max(2\alpha, \alpha')$ where α' is a predefined upper bound

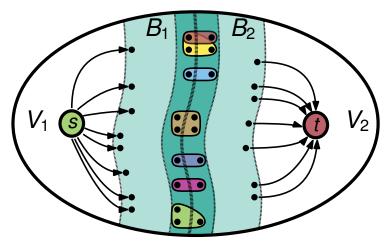
Otherwise, $\alpha = \min(\frac{\alpha}{2}, 1)$ B_2 Cut

Our Flow-Based Refinement Framework

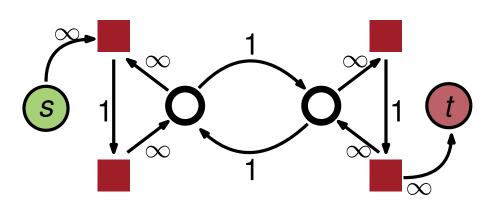




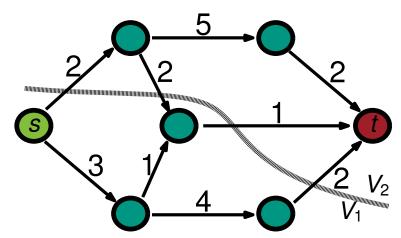
Select two adjacent blocks for refinement



Build Flow Problem



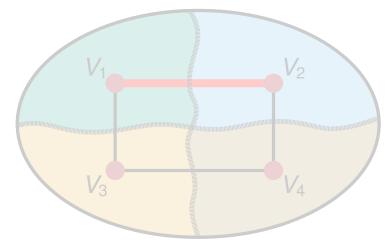
Solve Flow Problem



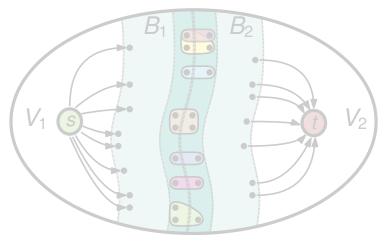
Find feasible minimum cut

Our Flow-Based Refinement Framework

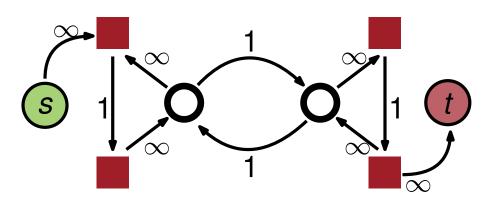




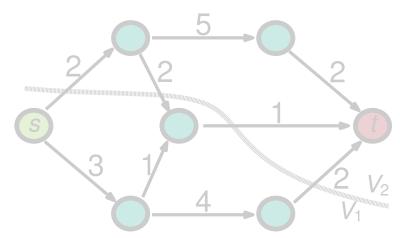
Select two adjacent blocks for refinement



Build Flow Problem

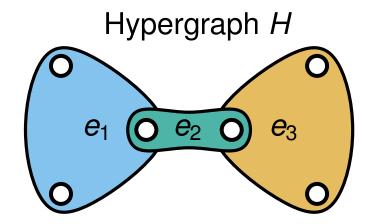


Solve Flow Problem

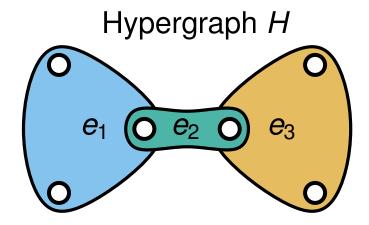


Find feasible minimum cut

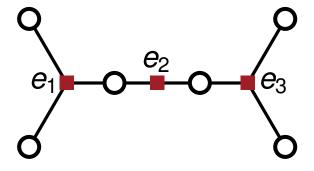




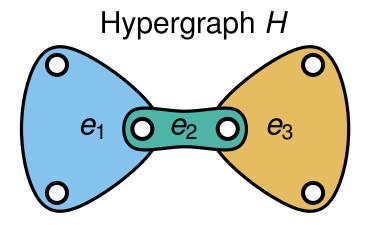




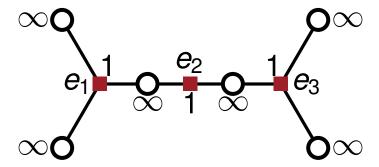
Bipartite Graph $G_*(H)$





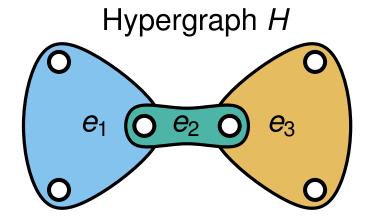


Bipartite Graph $G_*(H)$

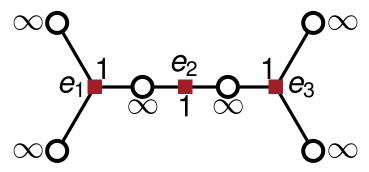


Vertex Separator Problem



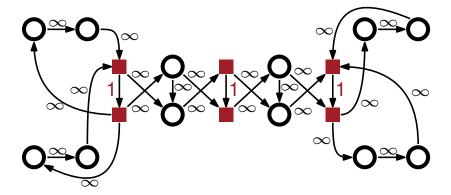


Bipartite Graph $G_*(H)$



Vertex Separator Problem

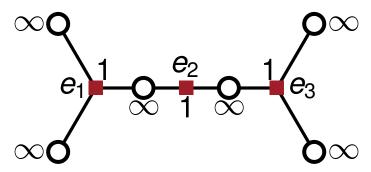
Vertex Separator Transformation





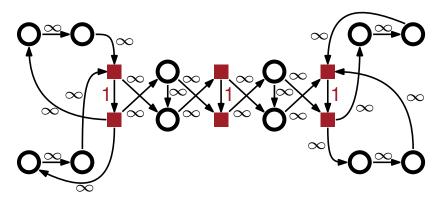
Hypergraph H $e_1 \bigcirc e_2 \bigcirc e_3$

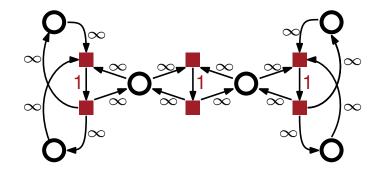
Bipartite Graph $G_*(H)$



Vertex Separator Problem

Vertex Separator Transformation



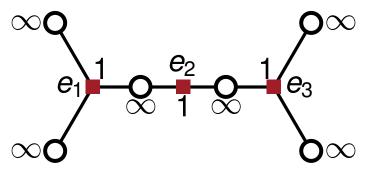




Hypergraph H

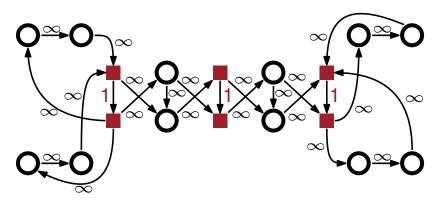
e₁ O e₂ O e₃

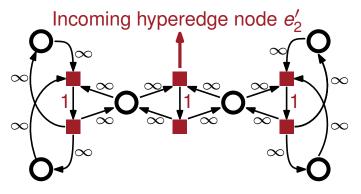
Bipartite Graph $G_*(H)$



Vertex Separator Problem

Vertex Separator Transformation



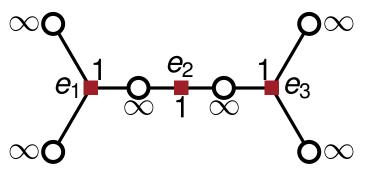




Hypergraph H

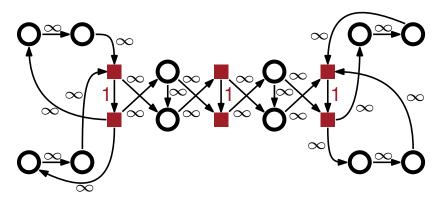
e₁ O e₂ O e₃

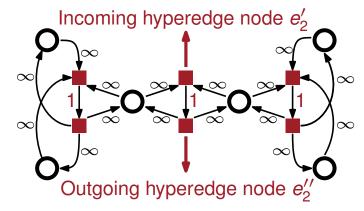
Bipartite Graph $G_*(H)$



Vertex Separator Problem

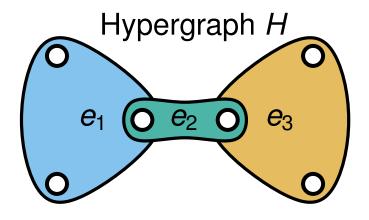
Vertex Separator Transformation



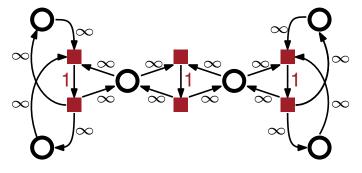


Hypergraph Flow Network - Graph Edges



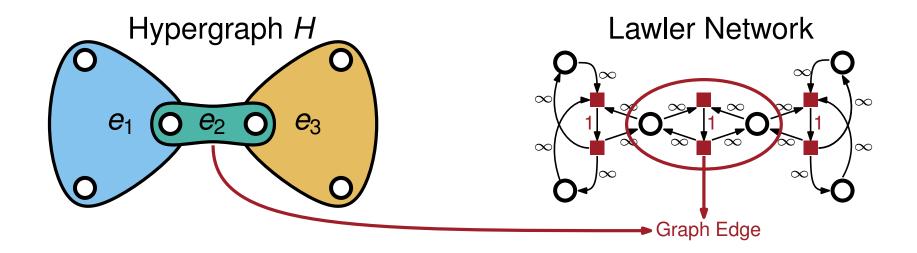


Lawler Network



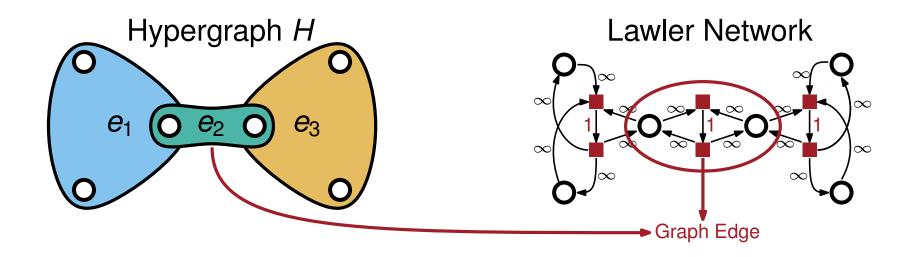
Hypergraph Flow Network - Graph Edges



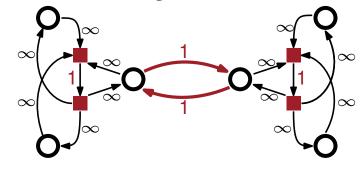


Hypergraph Flow Network - Graph Edges

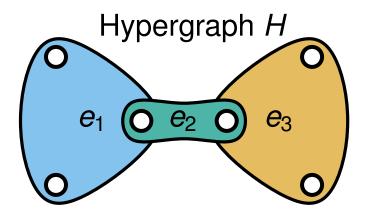


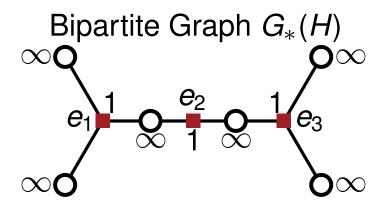


Wong Network

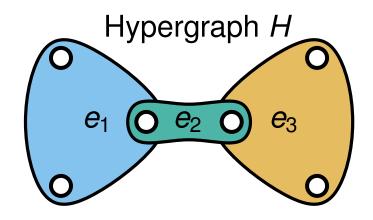


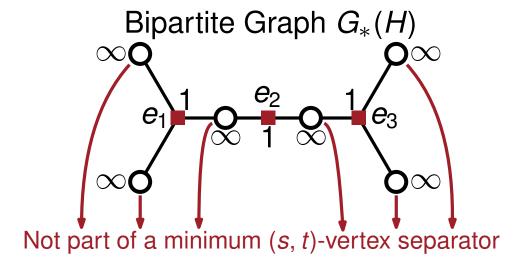




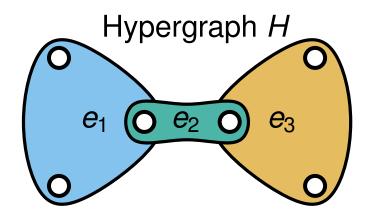


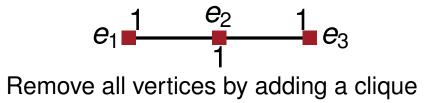




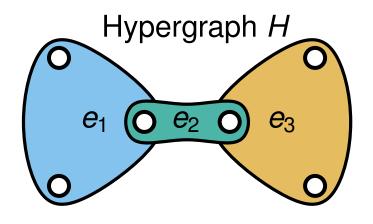


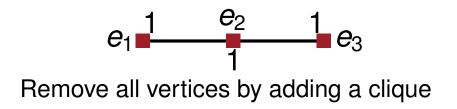




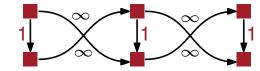




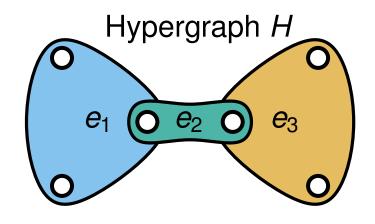


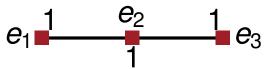


Our Network



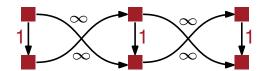






Remove all vertices by adding a clique

Our Network

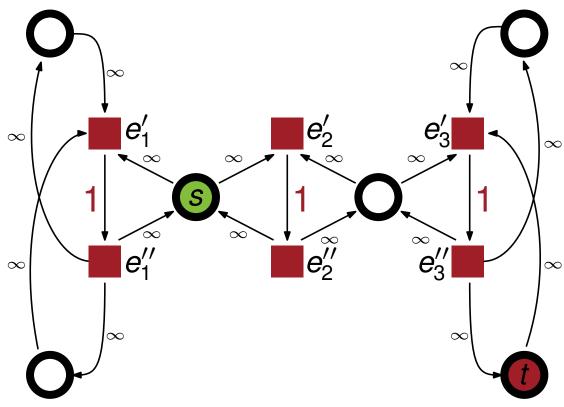


A hypernode *v* induces . . .

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

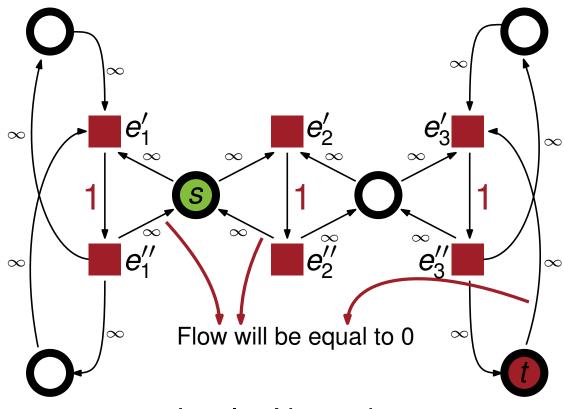
If $d(v) \leq 3$, then $d(v)(d(v) - 1) \leq 2d(v)$





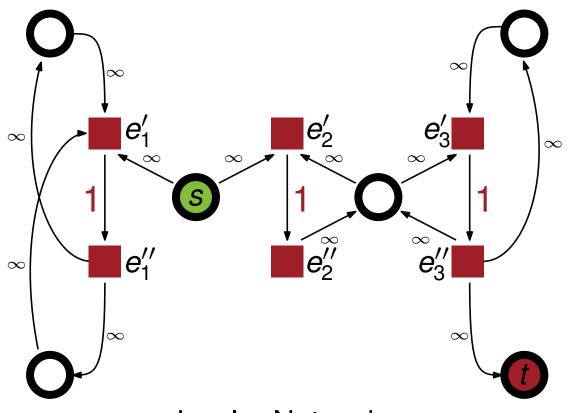
Lawler Network





Lawler Network

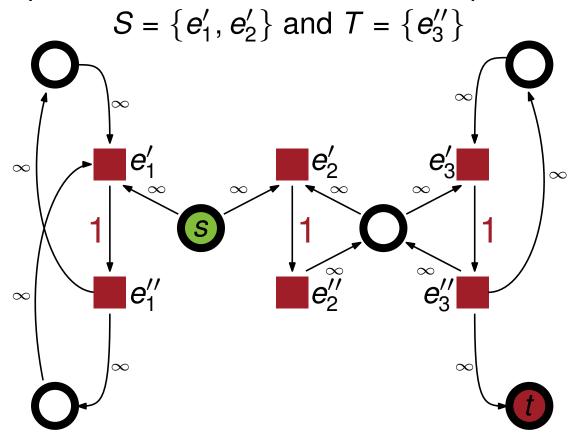




Lawler Network

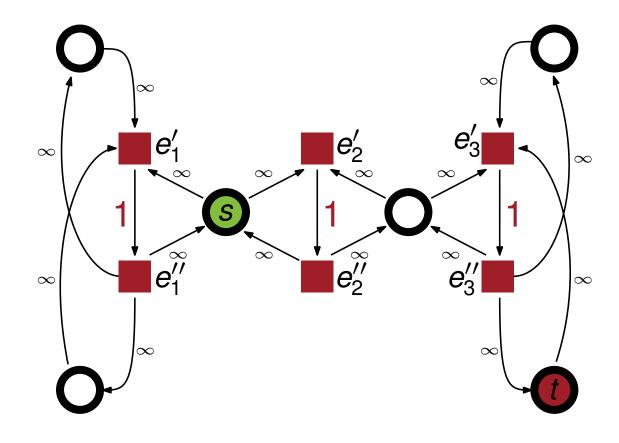


Corresponds to Multi-Source Multi-Sink problem with



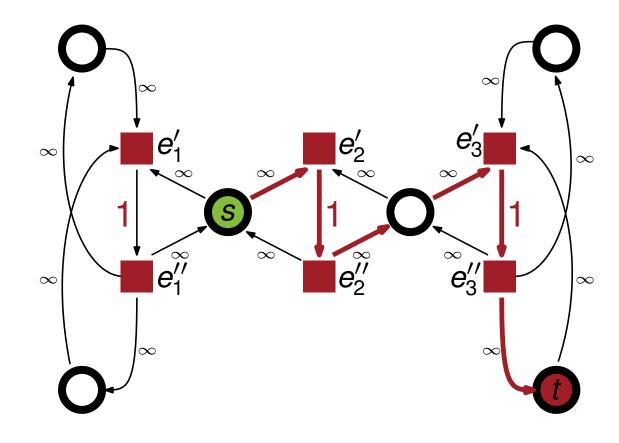
Minimum (s, t)-Bipartition





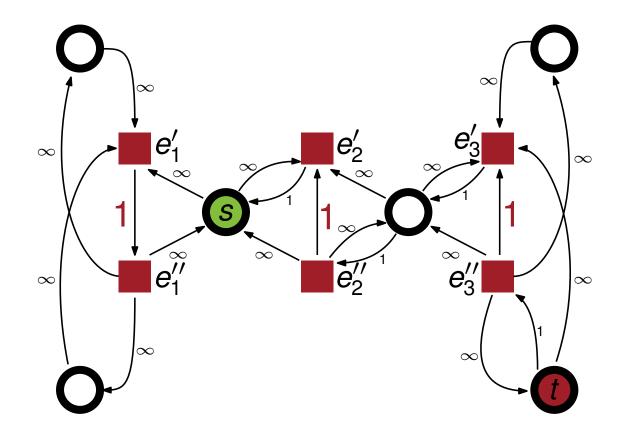
Minimum (s, t)-Bipartition



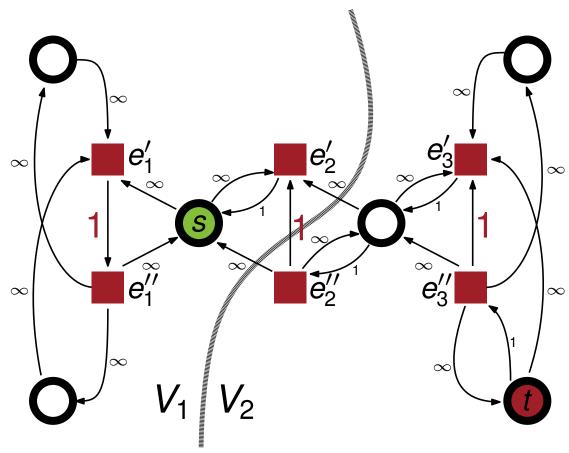


Minimum (s, t)-Bipartition





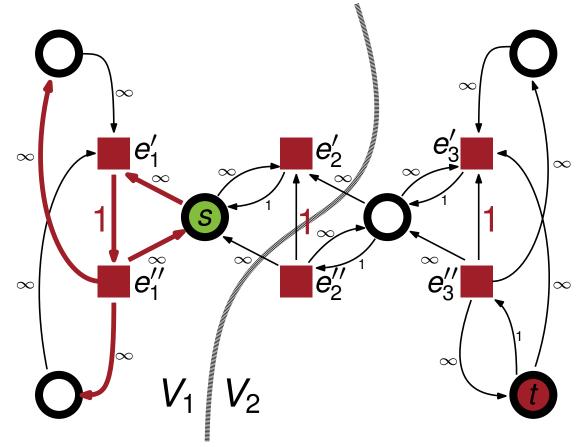




All nodes *reachable* from s are part of V_1 and $V_2 = V \setminus V_1$

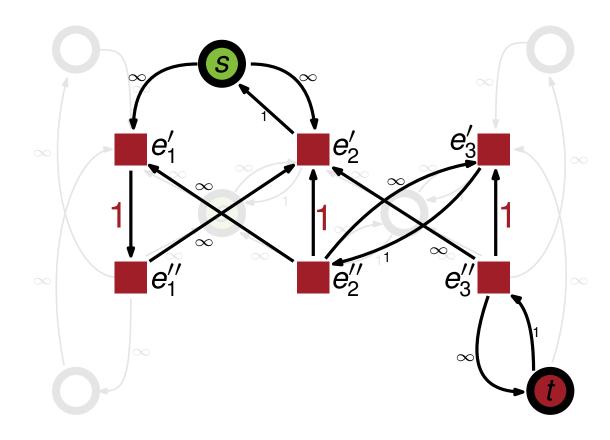


For each hypernode $v \in V_1$, there exists at least one $e \in I(v)$ with $e'' \in V_1$

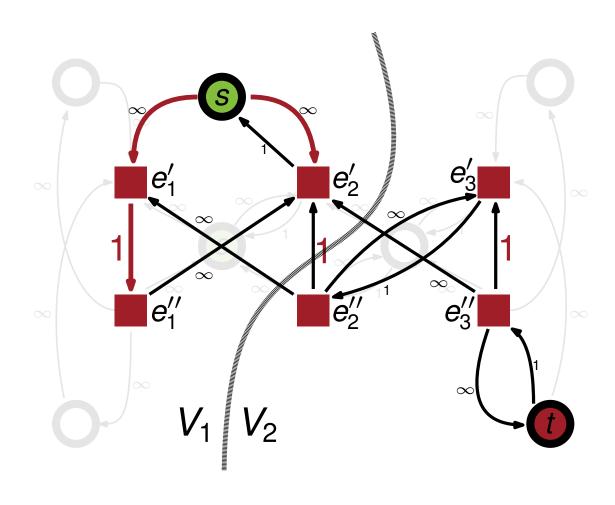


All nodes *reachable* from s are part of V_1 and $V_2 = V \setminus V_1$

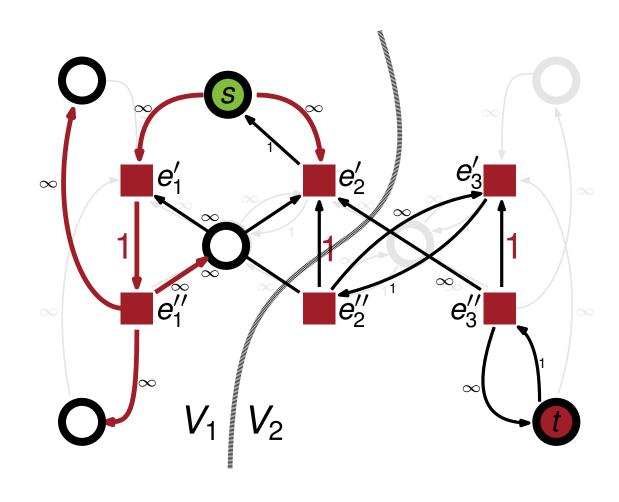




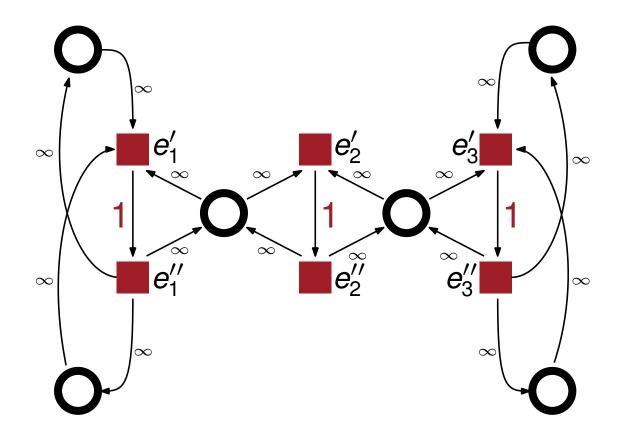








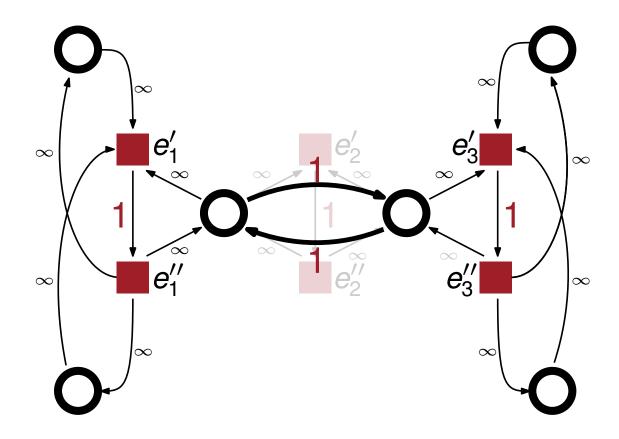




Lawler Network

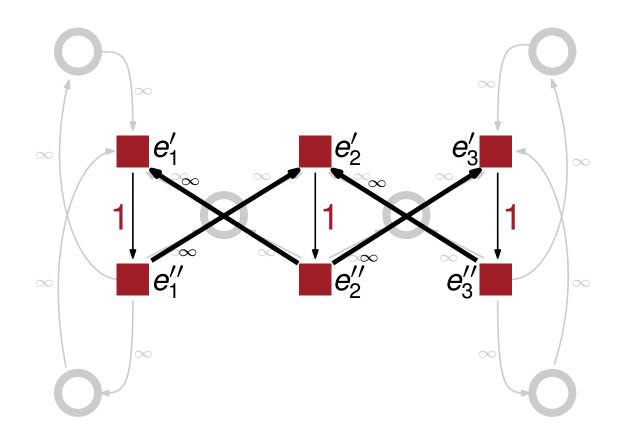






Wong Network

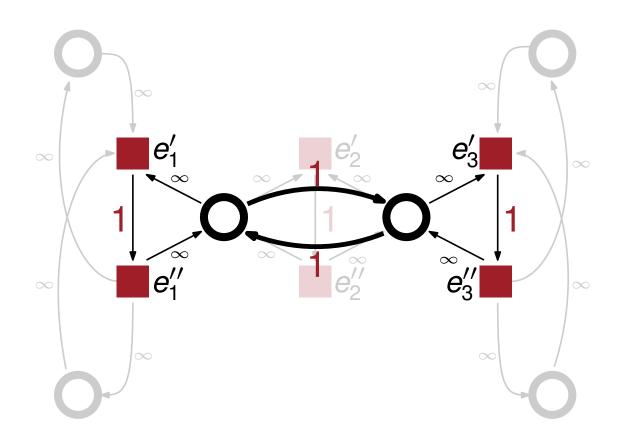




Our Network



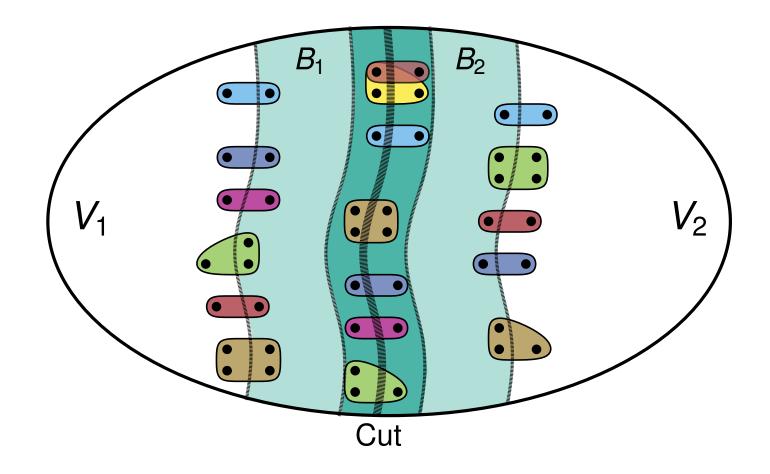




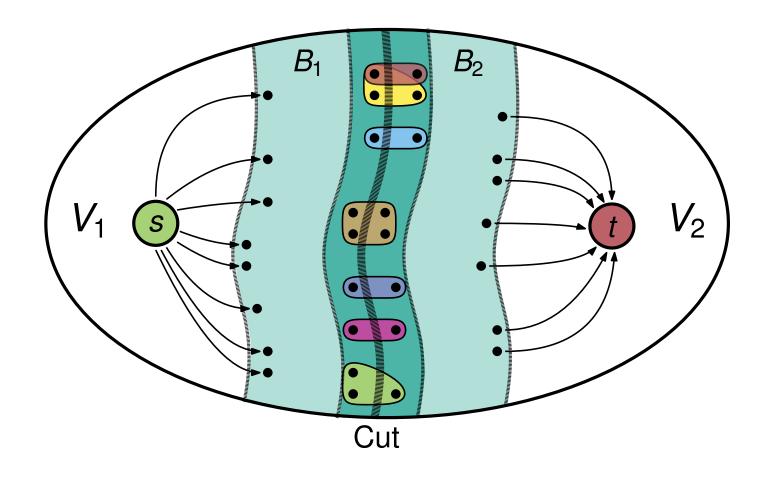
Hybrid Network









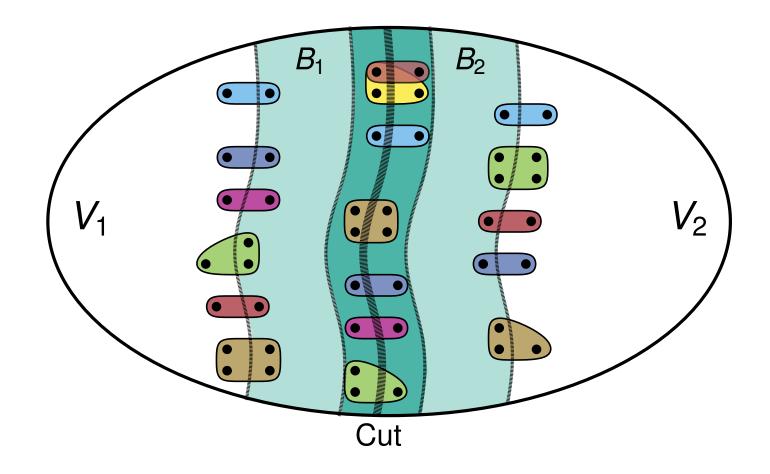




Modeling Approach in *KaFFPa*

Not moveable after Max-Flow-Min-Cut computation B_1 B_2 Cut

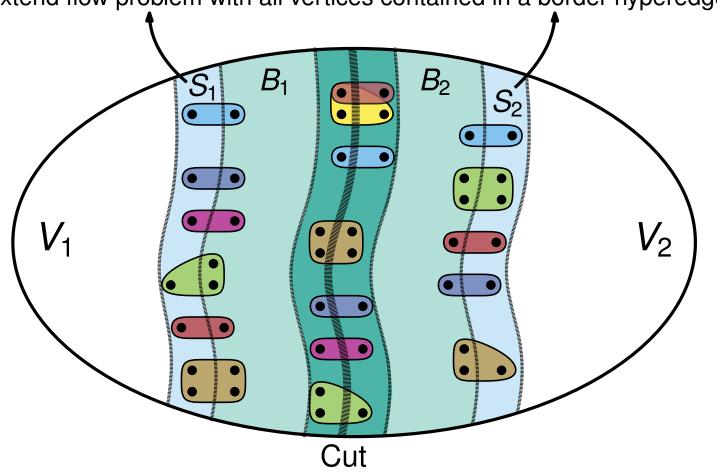




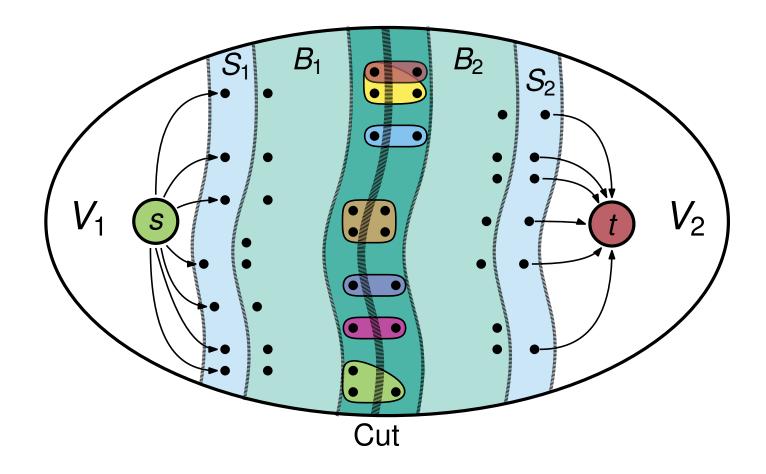


Modeling Approach in KaHyPar

Extend flow problem with all vertices contained in a border hyperedge



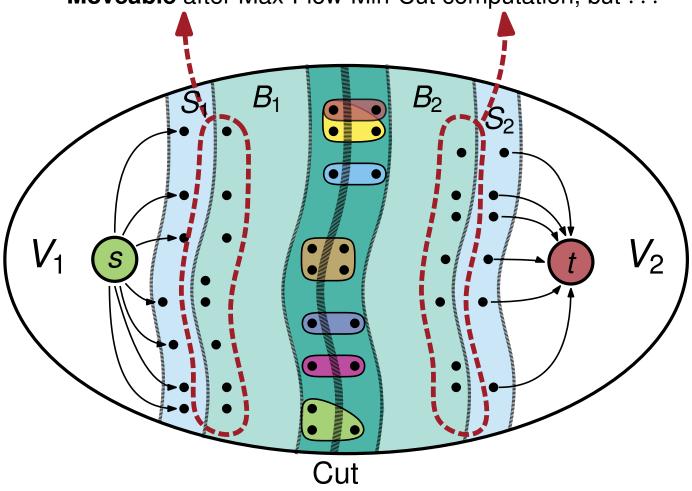






Modeling Approach in KaHyPar

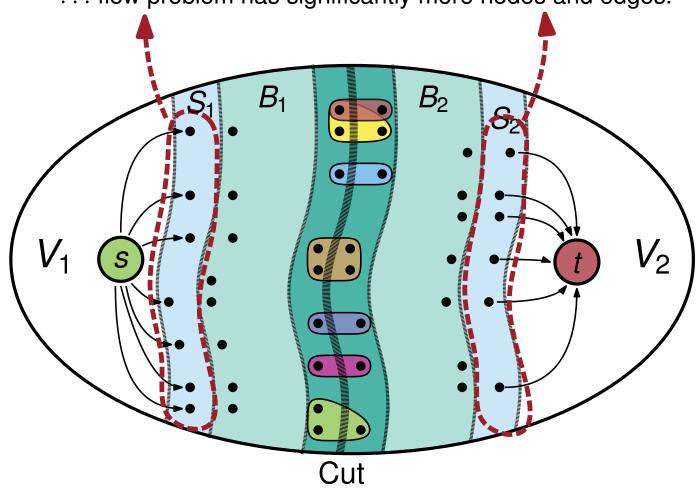
Moveable after Max-Flow-Min-Cut computation, but . . .



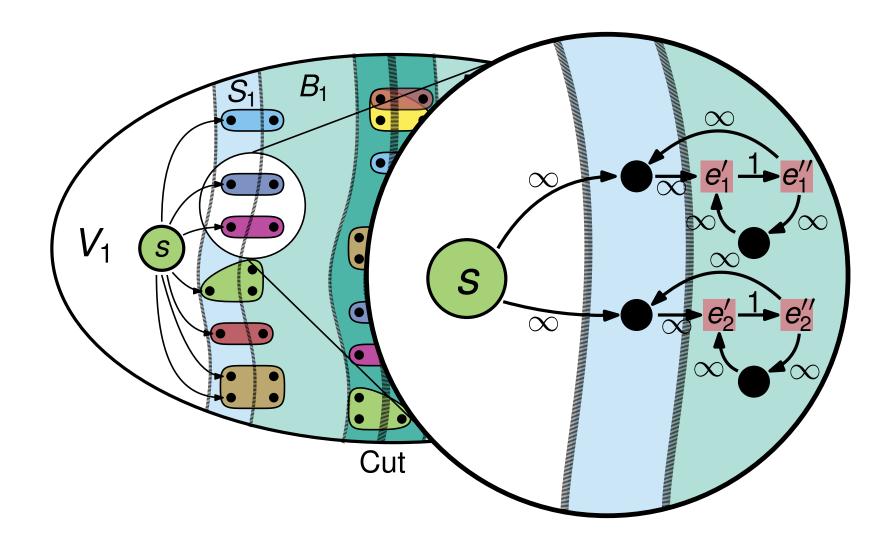


Modeling Approach in KaHyPar

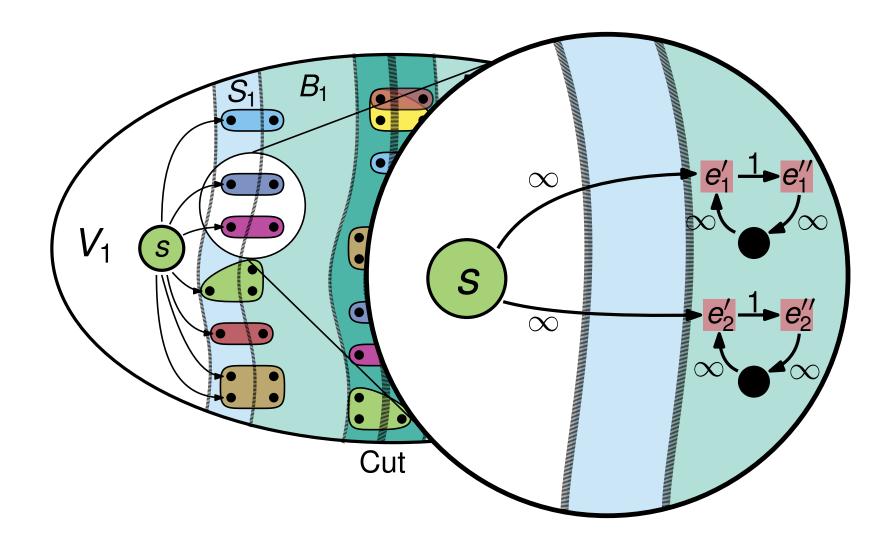
... flow problem has significantly more nodes and edges.







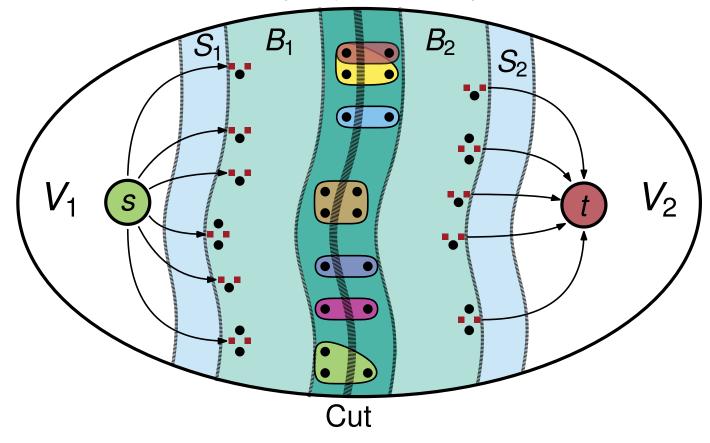






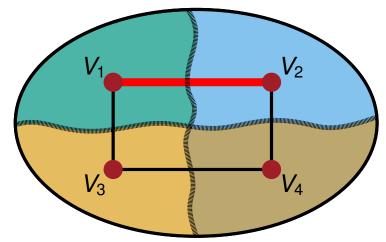
$$S = \{e' \mid e \in I(S_1)\}\$$

 $T = \{e'' \mid e \in I(S_2)\}\$

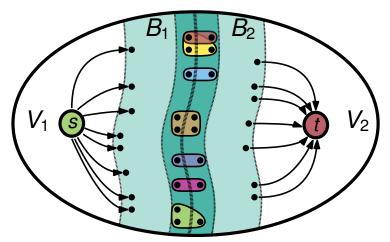


Our Flow-Based Refinement Framework

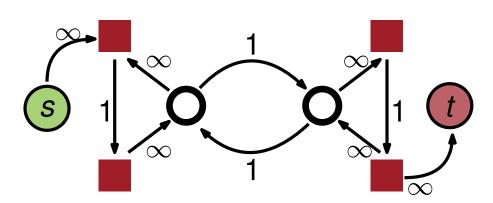




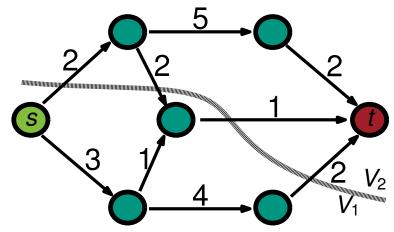
Select two adjacent blocks for refinement



Build Flow Problem



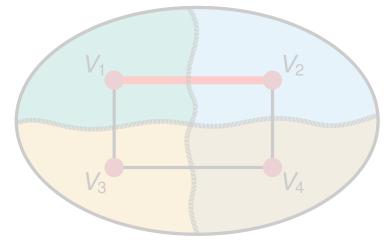
Solve Flow Problem



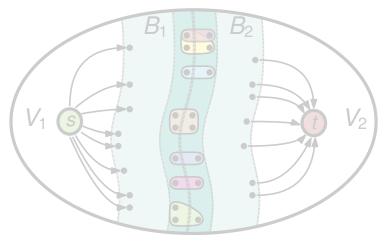
Find feasible minimum cut

Our Flow-Based Refinement Framework

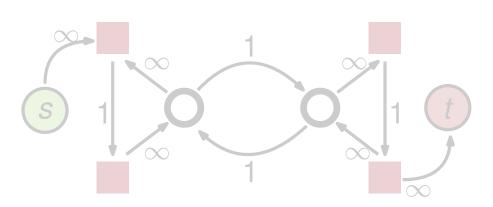




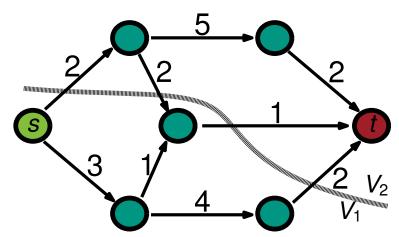
Select two adjacent blocks for refinement



Build Flow Problem



Solve Flow Problem



Find feasible minimum cut



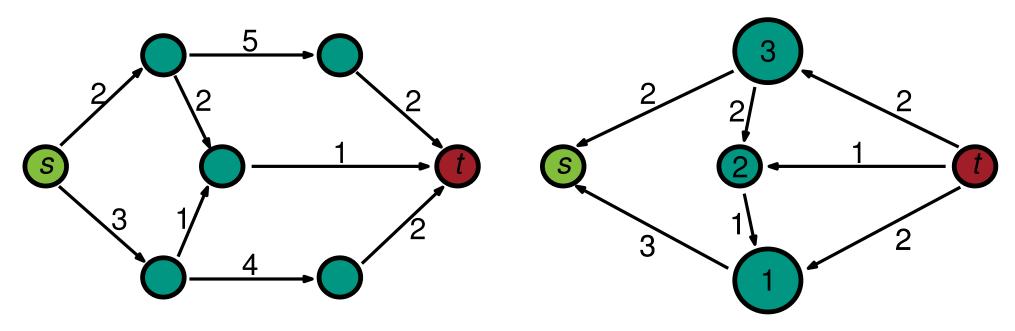
One maximum flow f has enough information to enumerate all minimum (s, t)-cuts



One maximum flow f has enough information to enumerate all minimum (s, t)-cuts



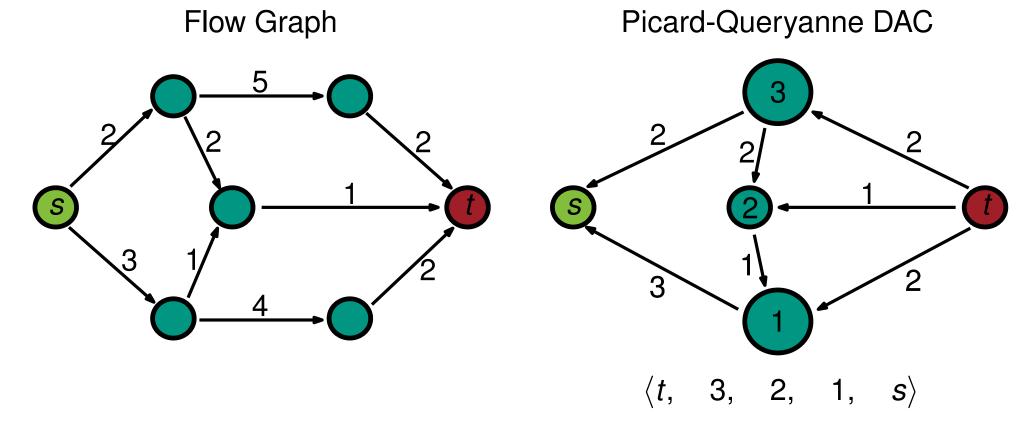
Picard-Queryanne DAC



Contract all strongly connected components in the residual graph



One maximum flow f has enough information to enumerate all minimum (s, t)-cuts

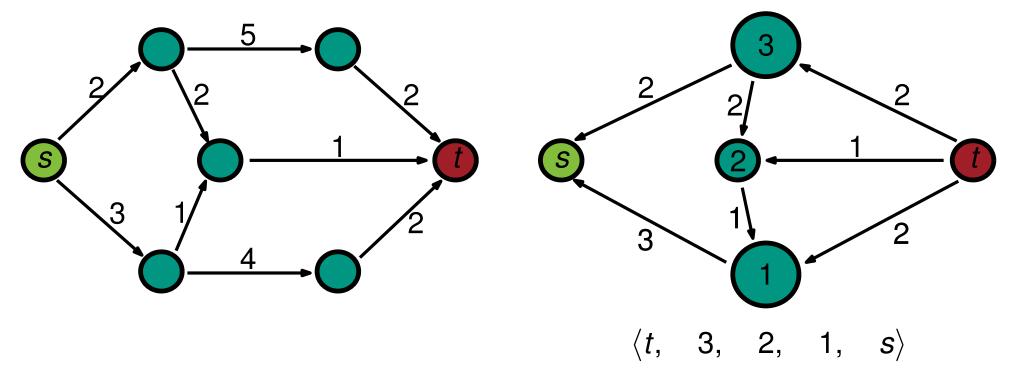


Find topological order



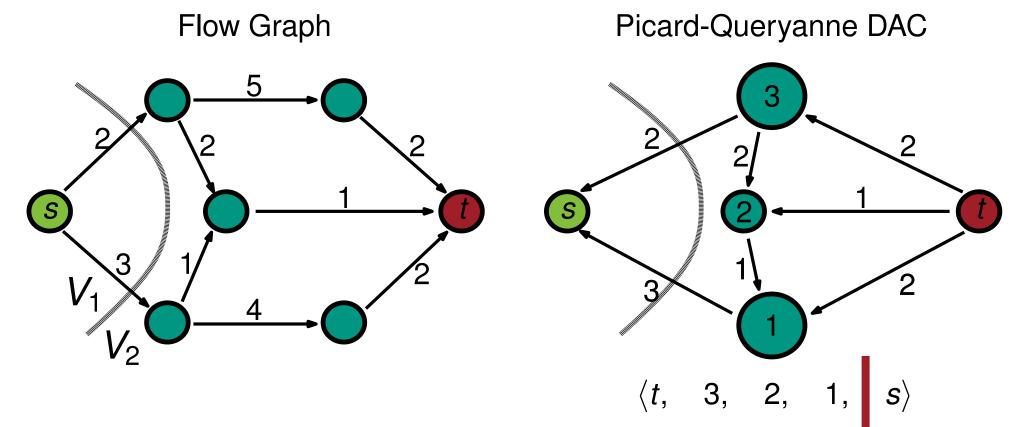
One maximum flow f has enough information to enumerate all minimum (s, t)-cuts

Flow Graph Picard-Queryanne DAC





One maximum flow f has enough information to enumerate all minimum (s, t)-cuts

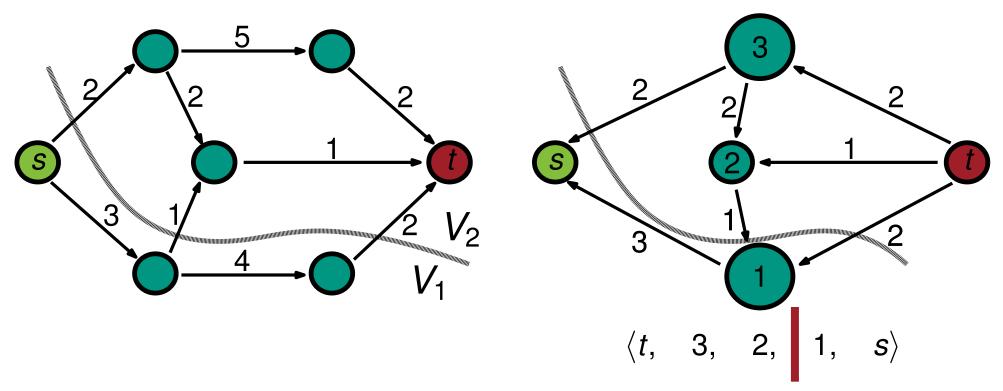




One maximum flow f has enough information to enumerate all minimum (s, t)-cuts

Flow Graph

Picard-Queryanne DAC

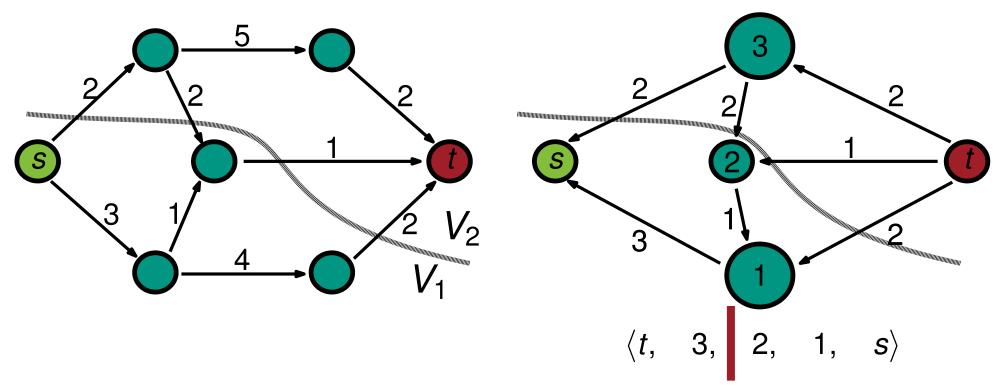




One maximum flow f has enough information to enumerate all minimum (s, t)-cuts

Flow Graph

Picard-Queryanne DAC





One maximum flow f has enough information to enumerate all minimum (s, t)-cuts

Flow Graph Picard-Queryanne DAC

