

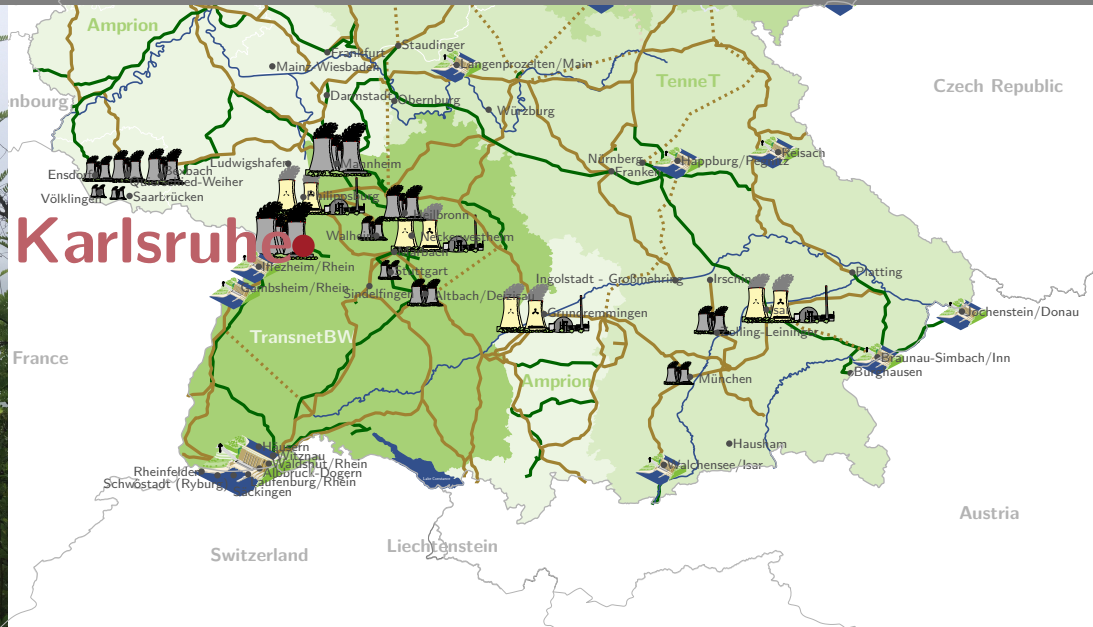
# Analogies to the Power Flow

## Towards Algorithms for the Power Flow and Maximum Power Flow Problem

CONDYNET2 · Focus Workshop · July 22th, 2019

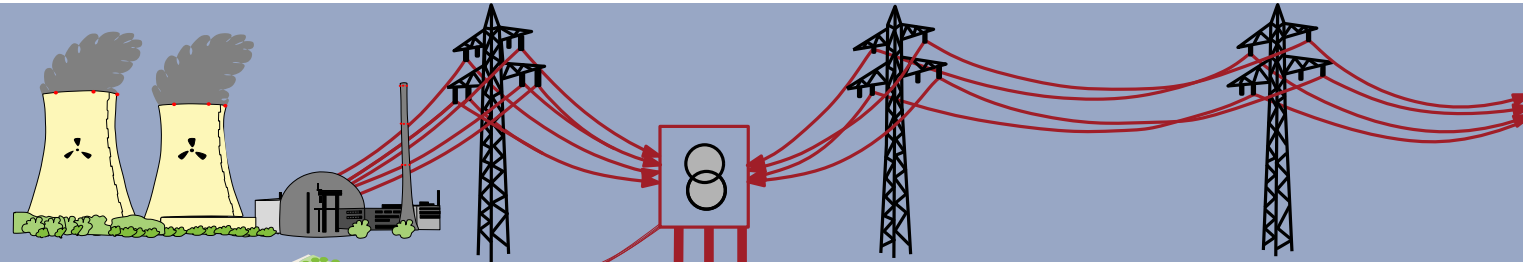
Franziska Wegner

INSTITUTE OF THEORETICAL INFORMATICS · ALGORITHMICS GROUP

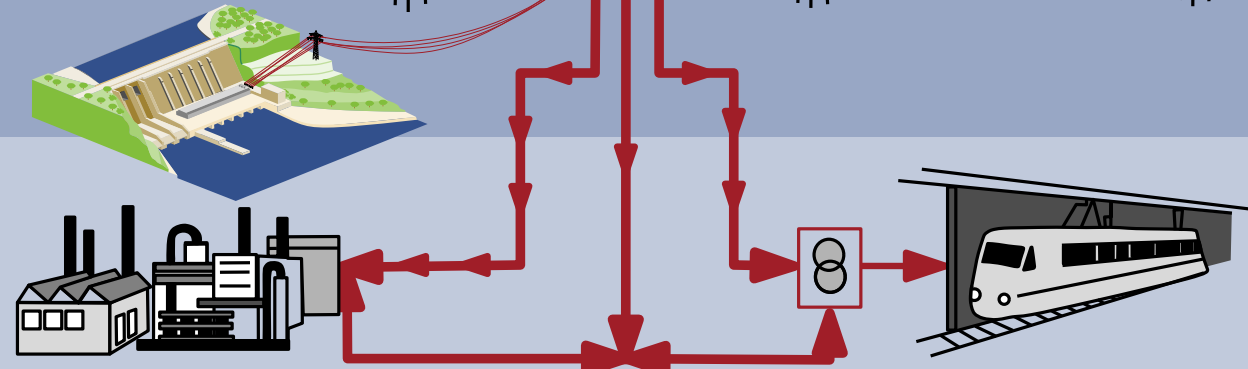


# Recent Development in Power Grids

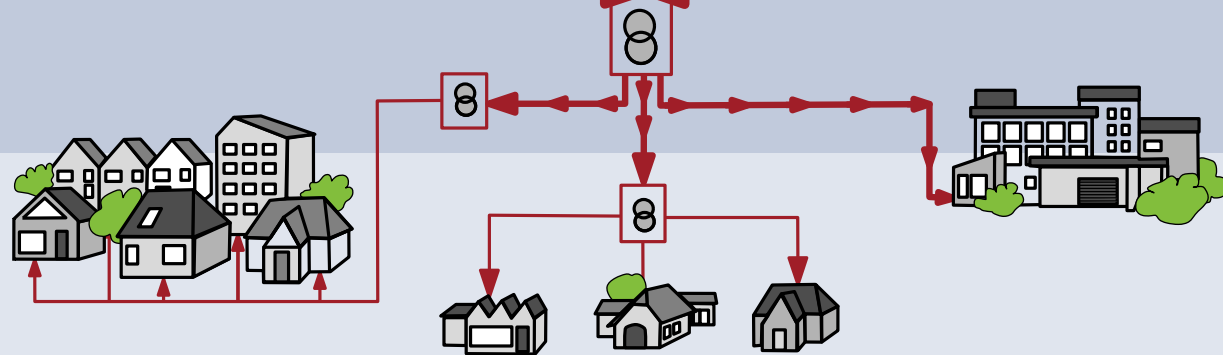
Producer



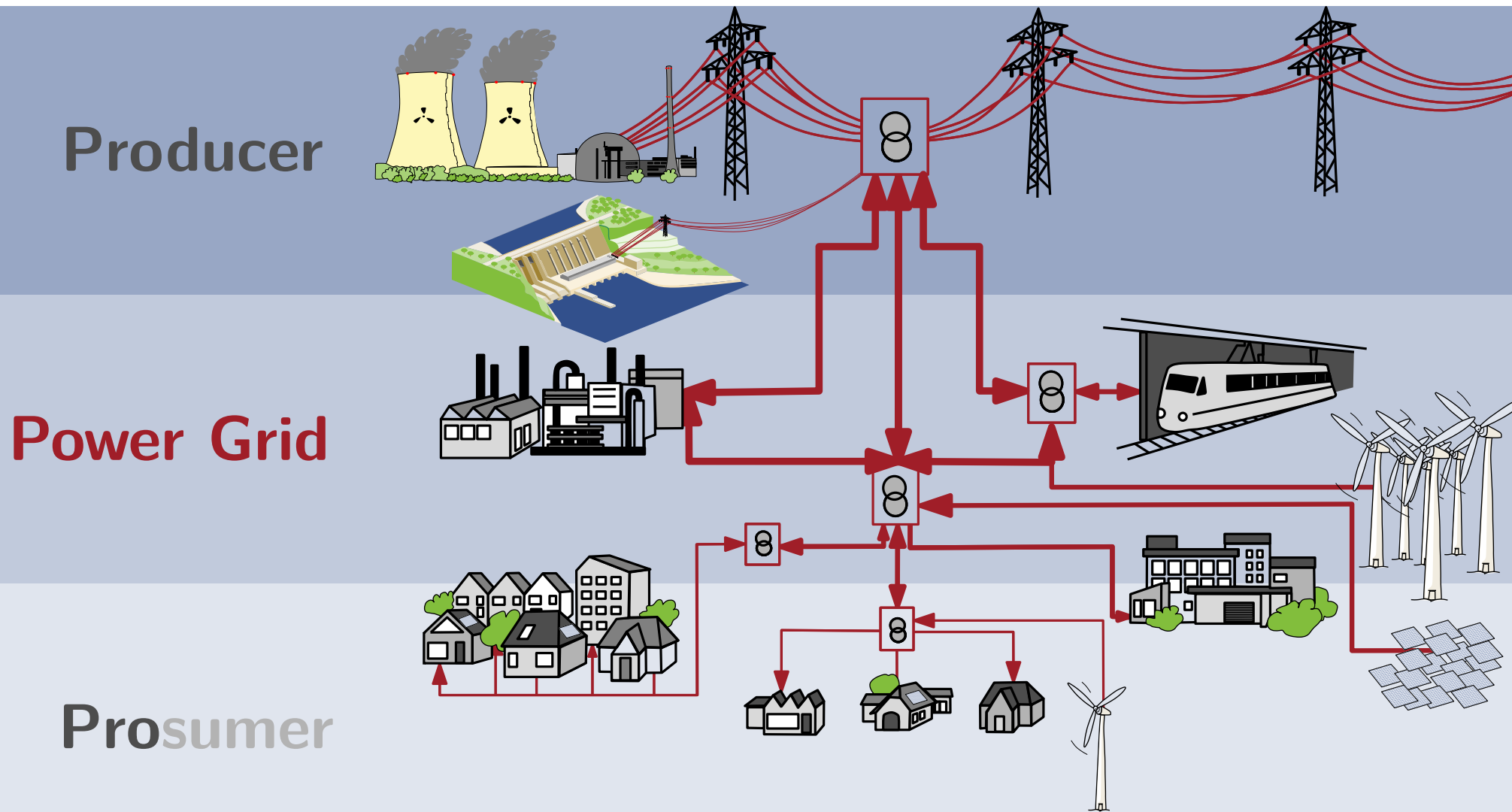
Power Grid



Consumer

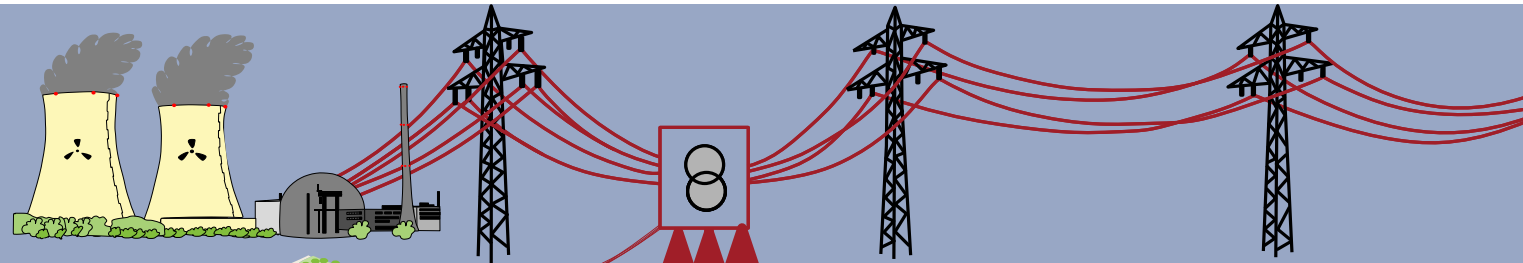


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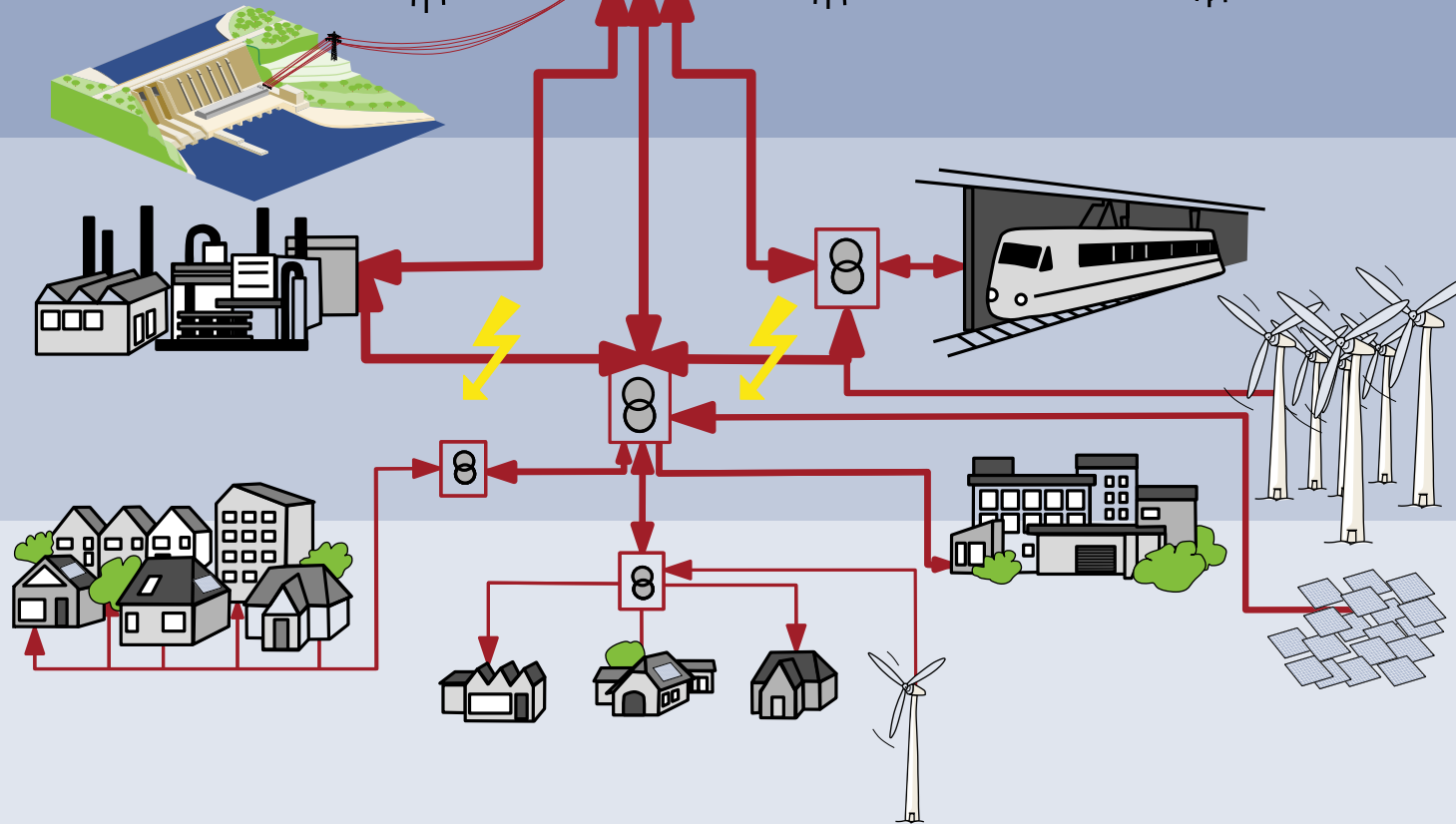


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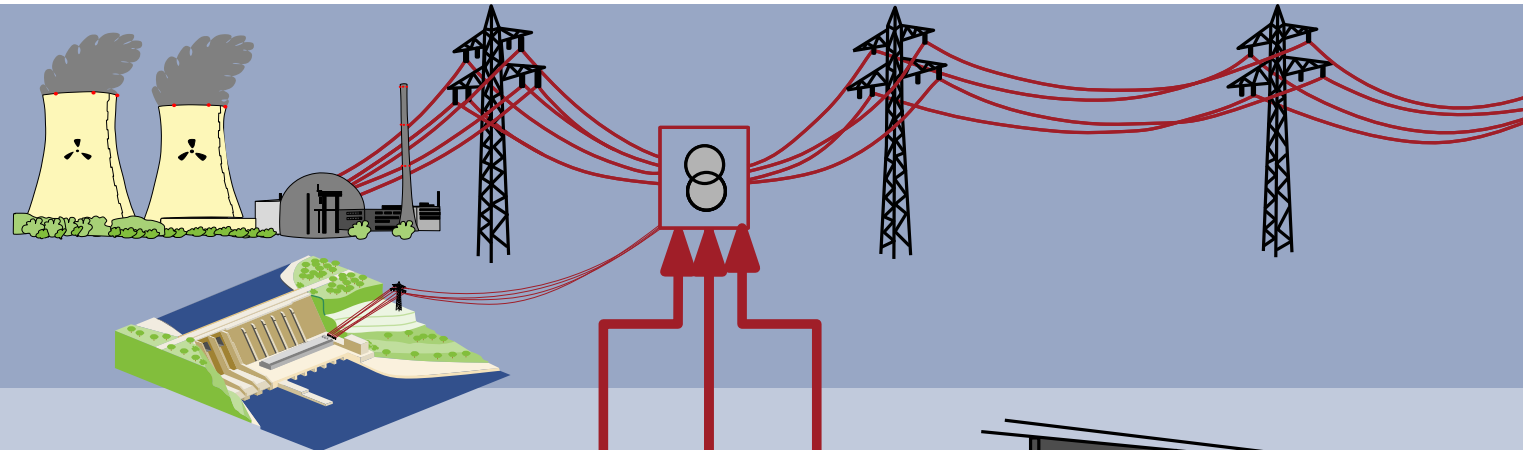
Power Grid



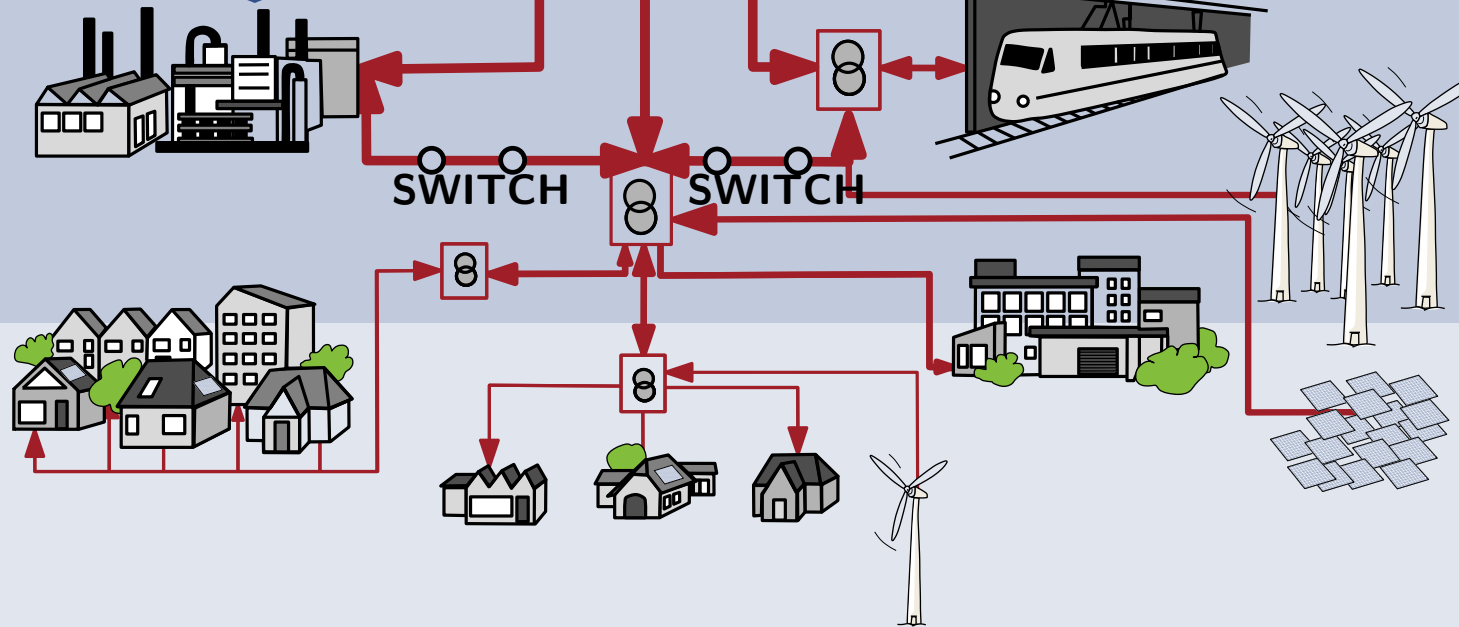
Prosumer

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Producer



Power Grid



Prosumer

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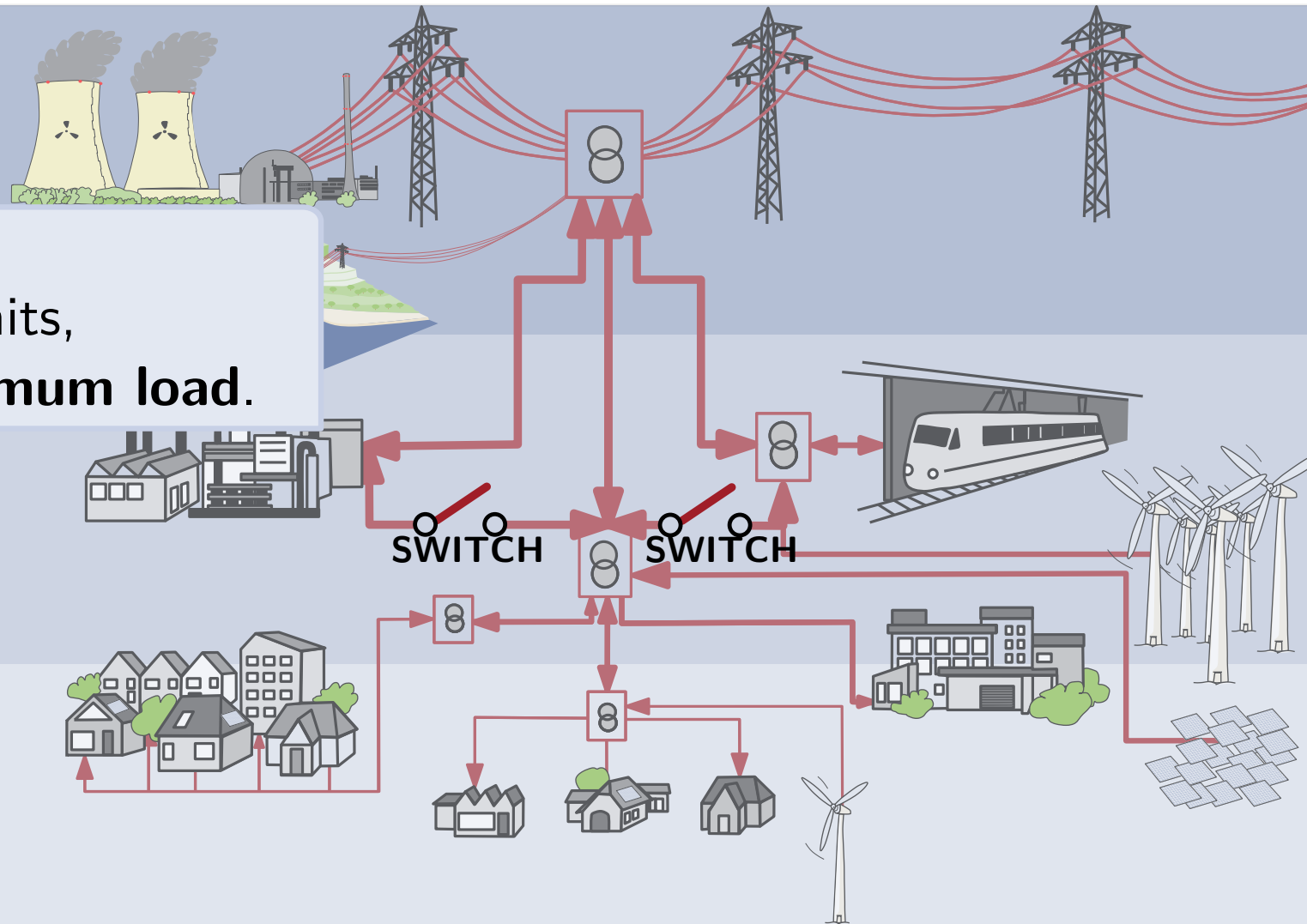
Producer

Switches...

- are **control** units,
- increase **maximum load**.

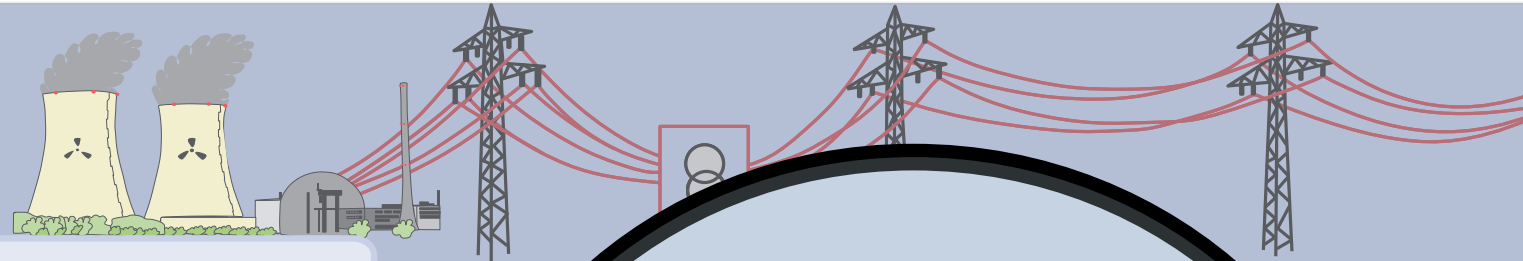
Power Grid

Prosumer



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Producer



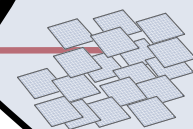
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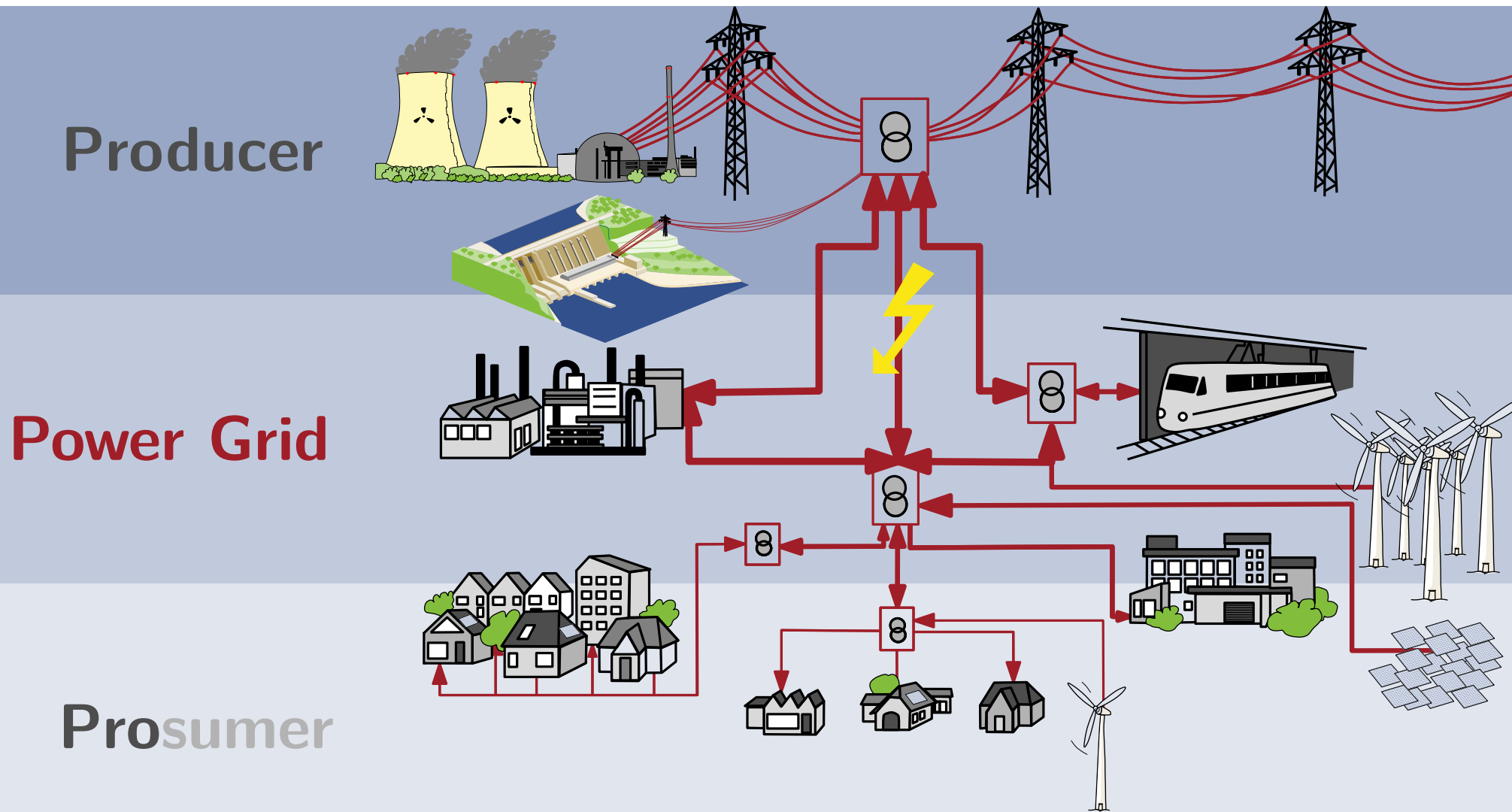
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Prosumer



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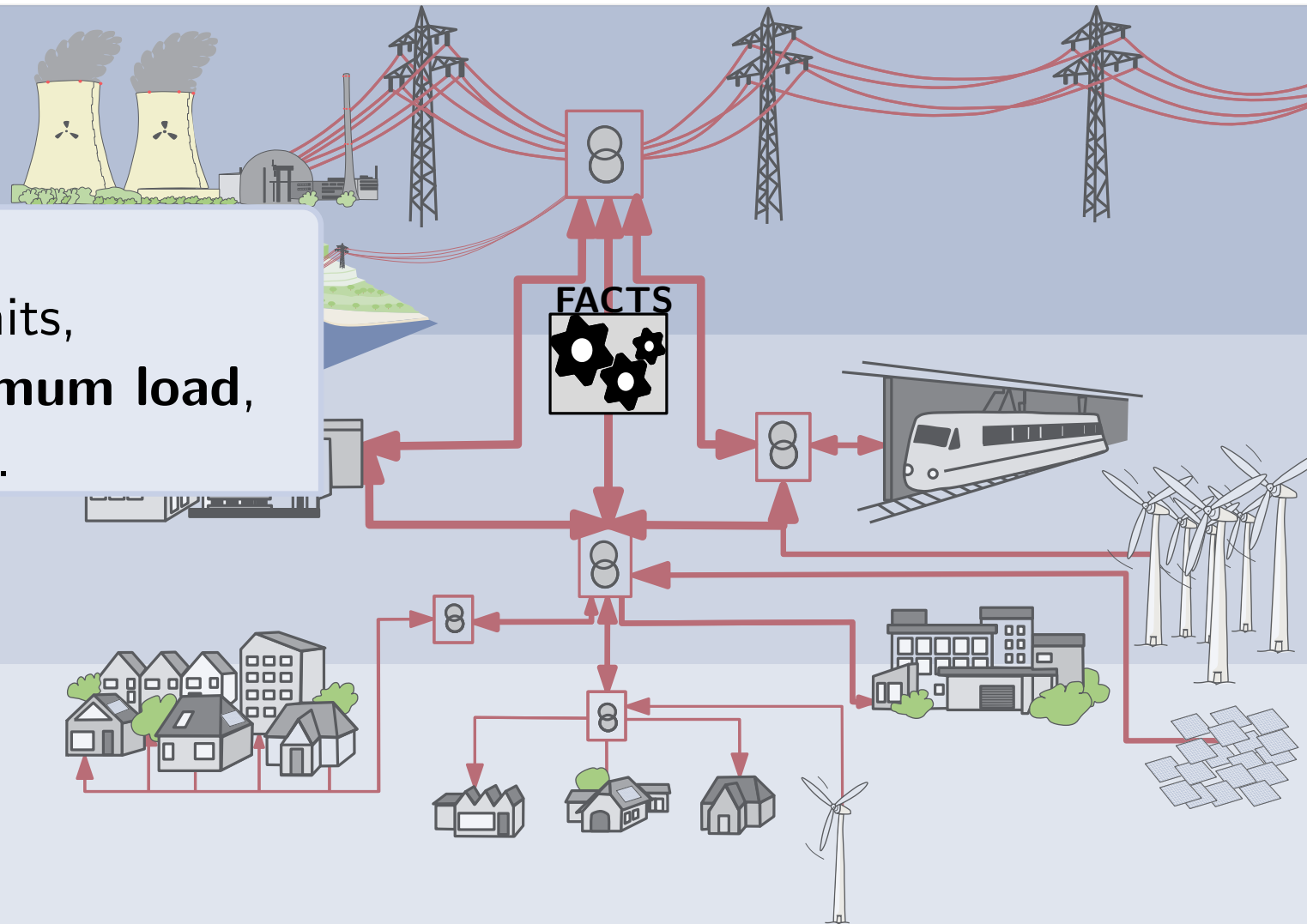
Producer

FACTS...

- are **control** units,
- increase **maximum load**,
- are **expensive**.

POWER GRID

Prosumer



# Recent Development in Power Grids

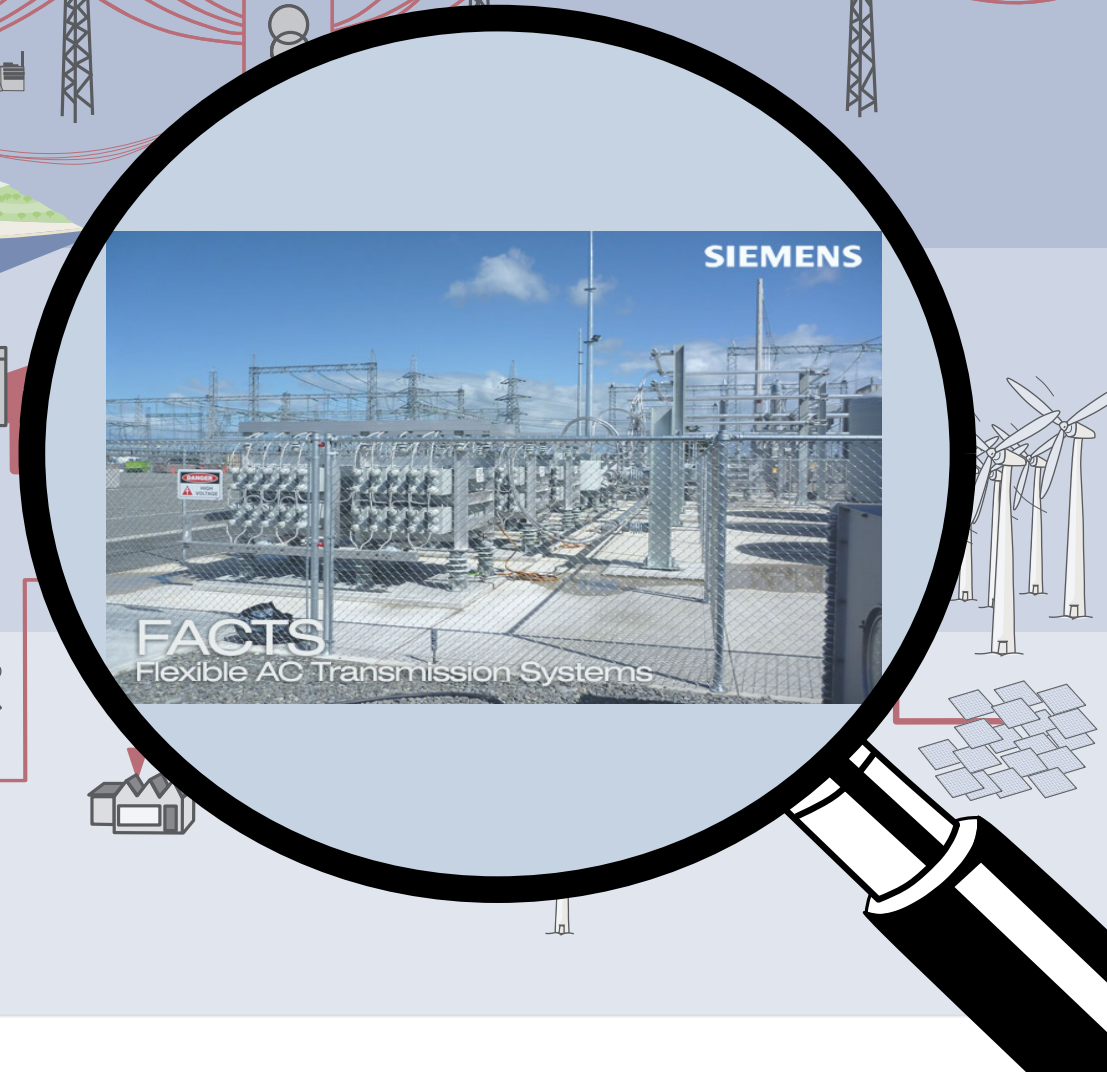
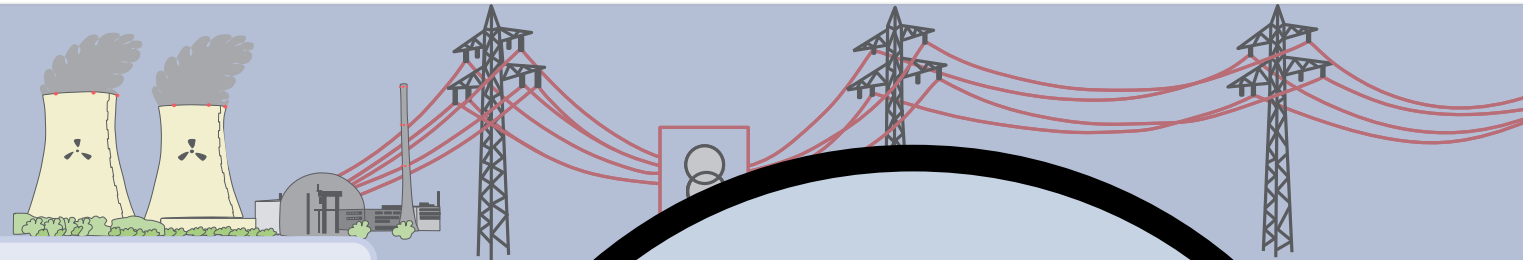
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FACTS...

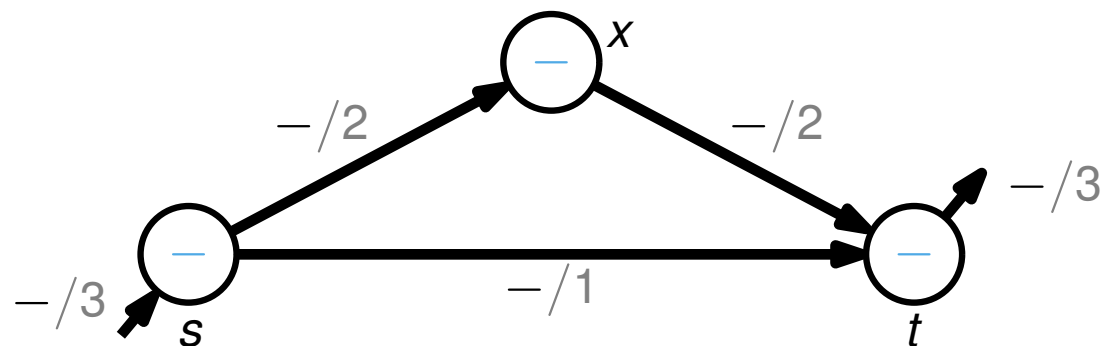
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POWER GRID

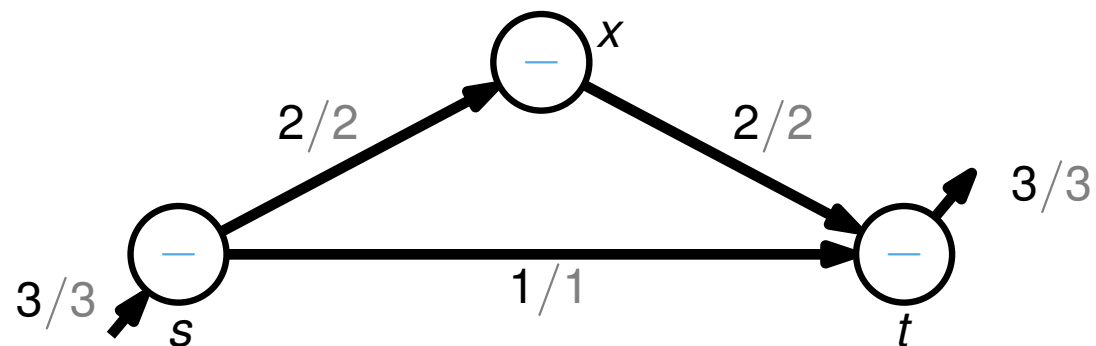
Prosumer



# The Maximum Flow Problem (MFP)

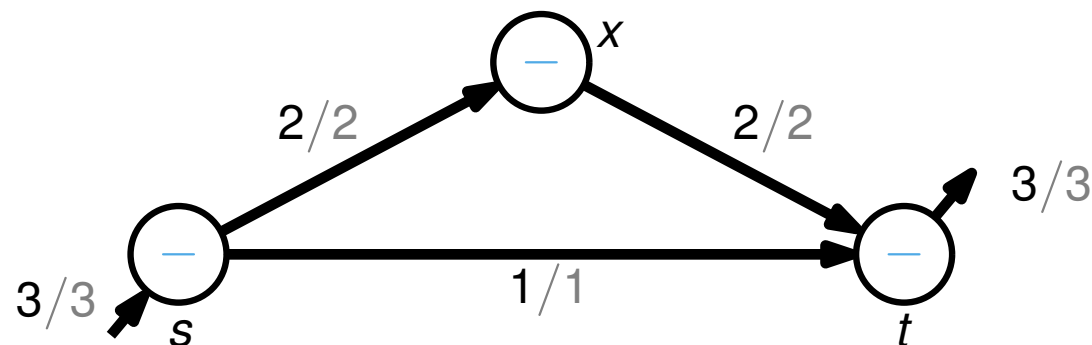


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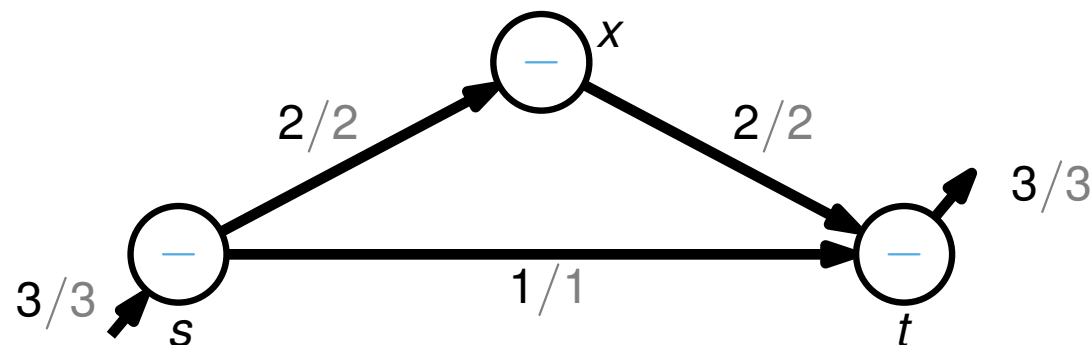
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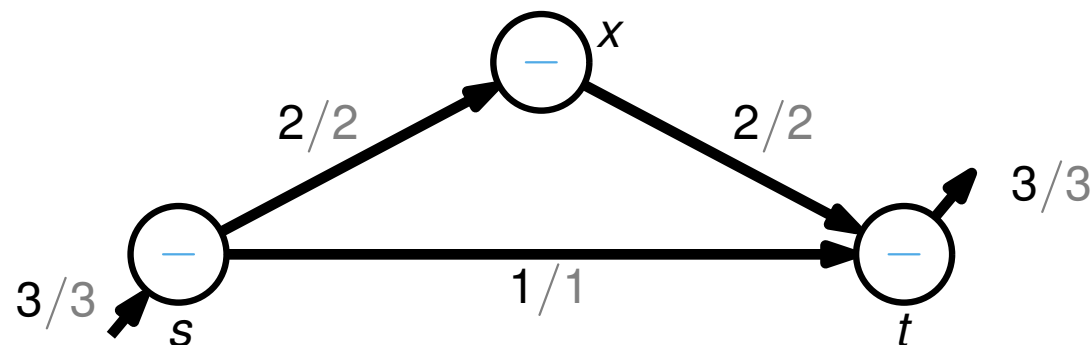
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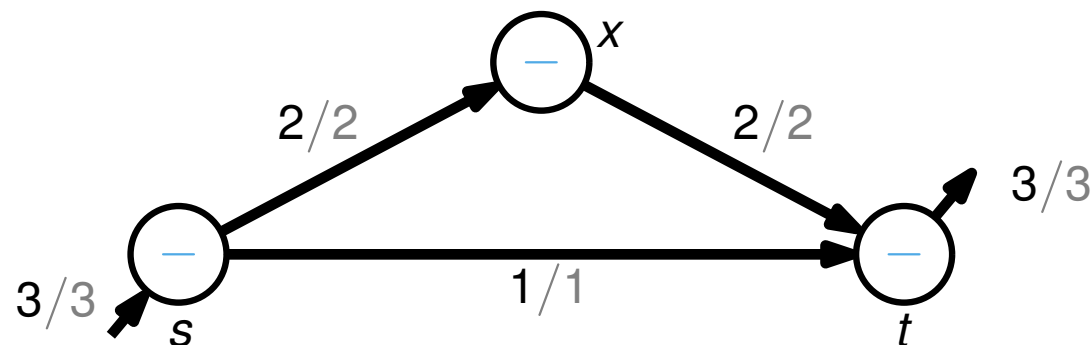
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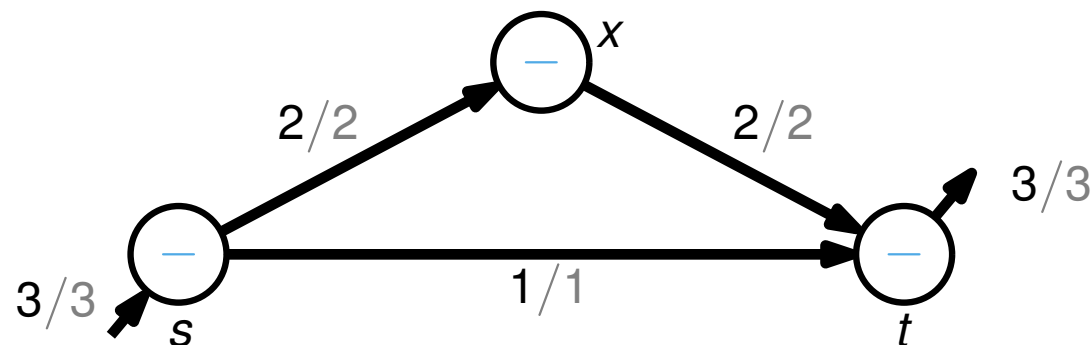




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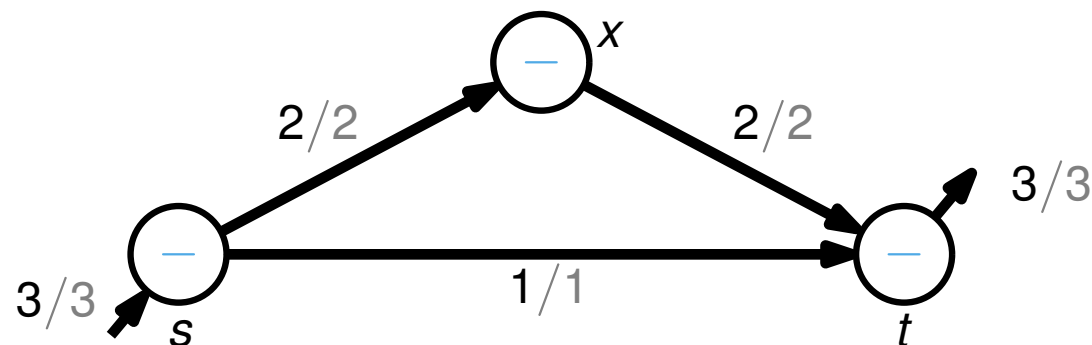
$$\begin{aligned} f_{\text{net}}(u) &= \sum_{\{u,v\} \in E} f(u,v) = 0 & \forall u \in V \setminus (V_G \cup V_D) \\ -\infty &\leq f_{\text{net}}(u) \leq -d & \forall u \in V_D \\ 0 &\leq f_{\text{net}}(u) \leq \infty & \forall u \in V_G \end{aligned}$$



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 |f(u,v)| &\leq \text{cap}(u,v) & \forall (u,v) \in E
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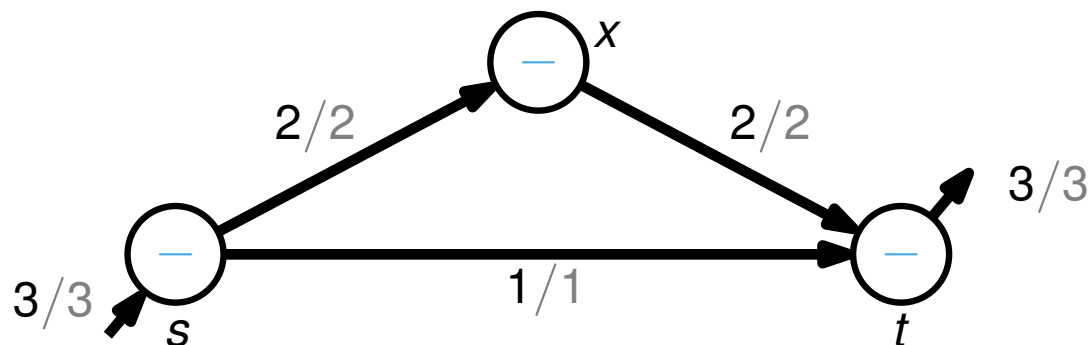
Conservation of Flow

$$f_{\text{net}}(u) = \sum_{\{u,v\} \in E} f(u,v) = 0 \quad \forall u \in V \setminus (V_G \cup V_D)$$

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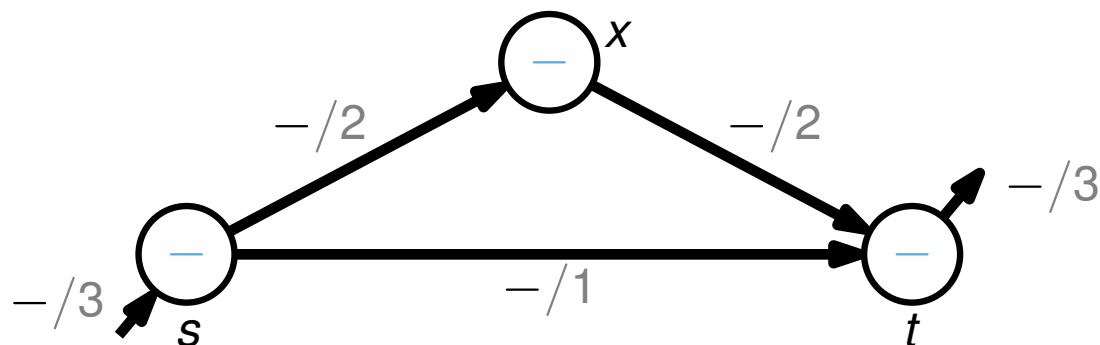


# Maximum Power Flow (MPF)

[Zimmerman et al., 2011]

A **feasible power flow** has to satisfy (additional) physical constraints:

- The Kirchhoff's Current Law (KCL) which relates to flow conservation, i.e.,  $f_{\text{net}}(u) = 0$  for all  $V \setminus (V_G \cup V_D)$

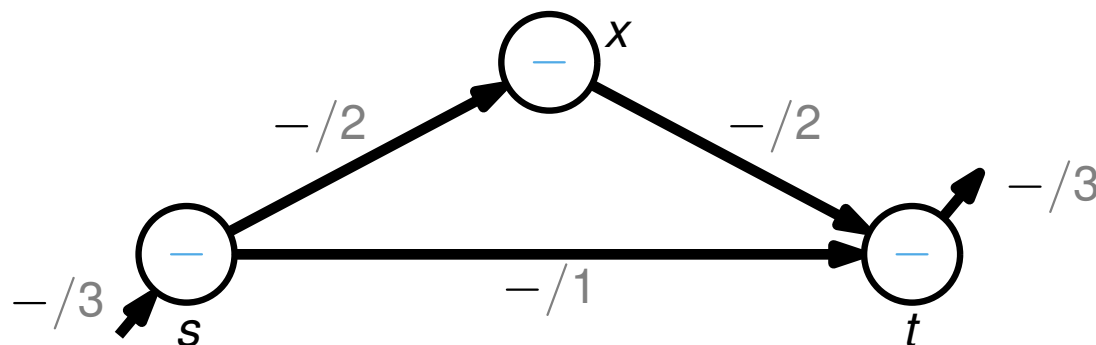


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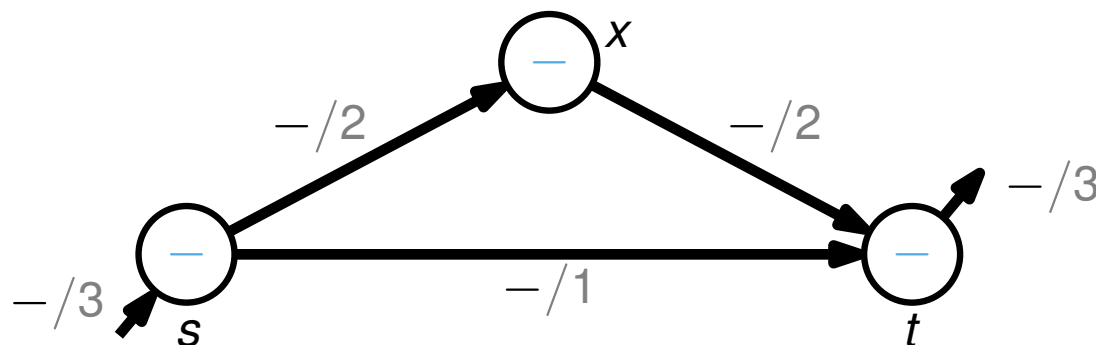
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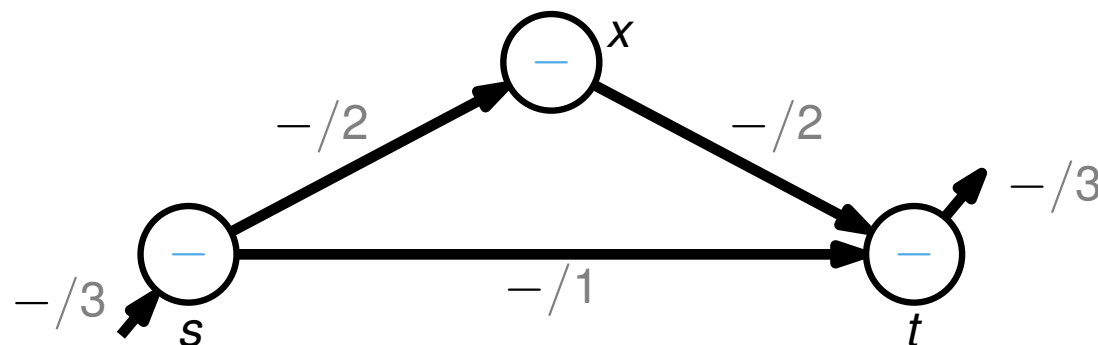
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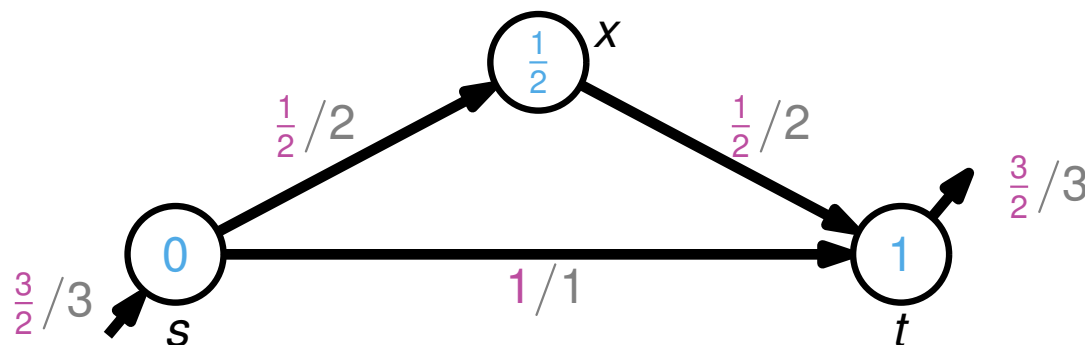
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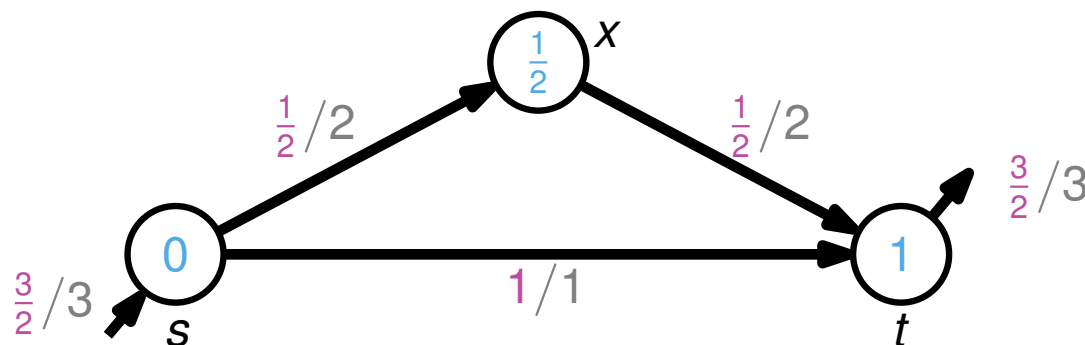
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$$\left. \begin{array}{l} (\theta(x) - \theta(s)) = f(s, x) \\ (\theta(t) - \theta(x)) = f(x, t) \end{array} \right\} (\theta(x) - \theta(s) + \theta(t) - \theta(x)) = f(s, x) + f(x, t)$$

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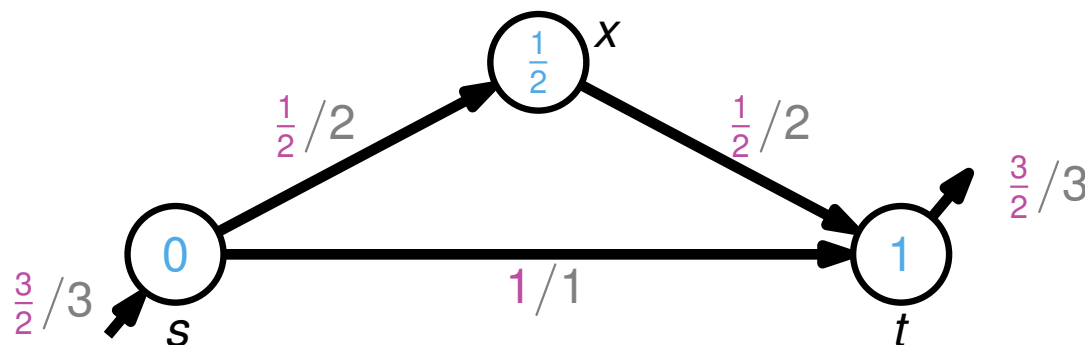
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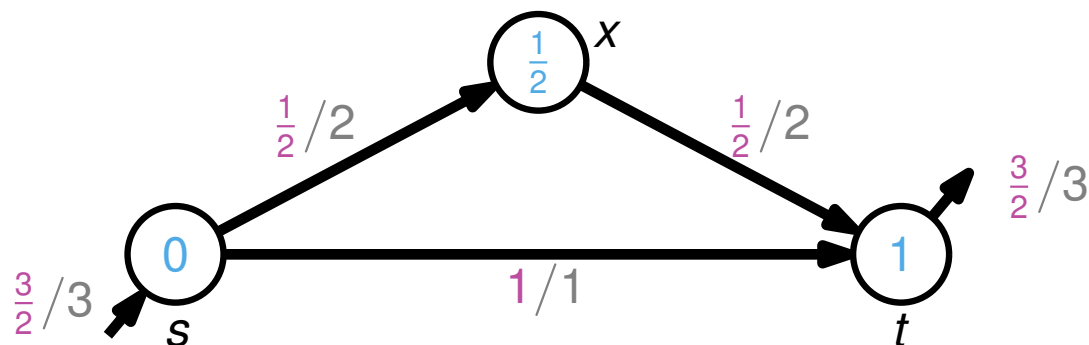
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- The value of the **MAXIMUM POWER FLOW** is defined as

$$\text{MPF}(\mathcal{N}) = \max F(\mathcal{N}, f)$$

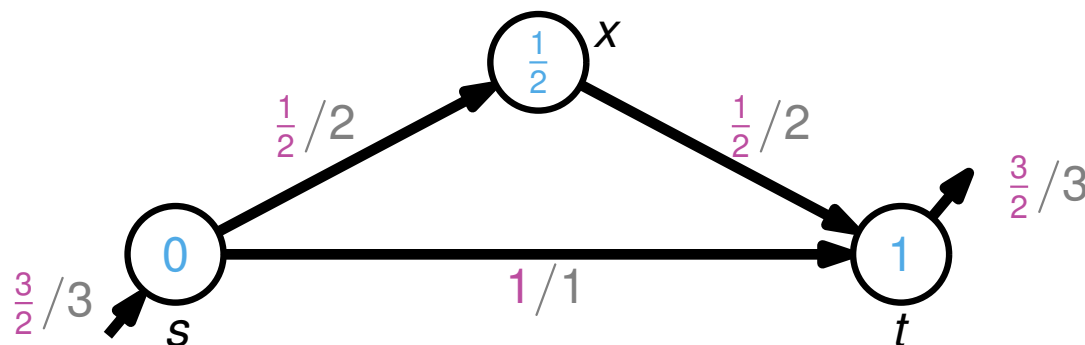
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## Vertex-based Formulation

## Vertex-/Cycle-based (Kirchhoff's) Formulation

$$f_{\text{net}}(u) = \sum_{\{u,v\} \in E} f(u, v) = 0$$

$$-\infty \leq f_{\text{net}}(u) \leq -d$$

$$0 \leq f_{\text{net}}(u) \leq \infty$$

$$\theta^v(v) - \theta^v(u) = f(u, v)$$

$$|f(u, v)| \leq \text{cap}(u, v)$$

**KCL**

**KVL**

$$\mathbf{I} \vec{f} = \vec{0}$$

$$\mathbf{B} \Delta \theta^v = \vec{0}$$

$$\vec{f} \leq \vec{\text{cap}}$$

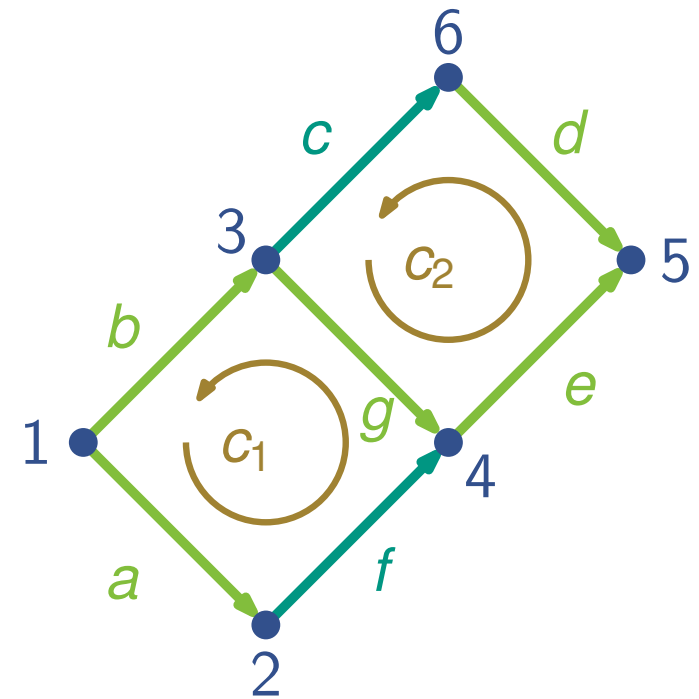
**I** – incidence matrix

**B** – circuite matrix

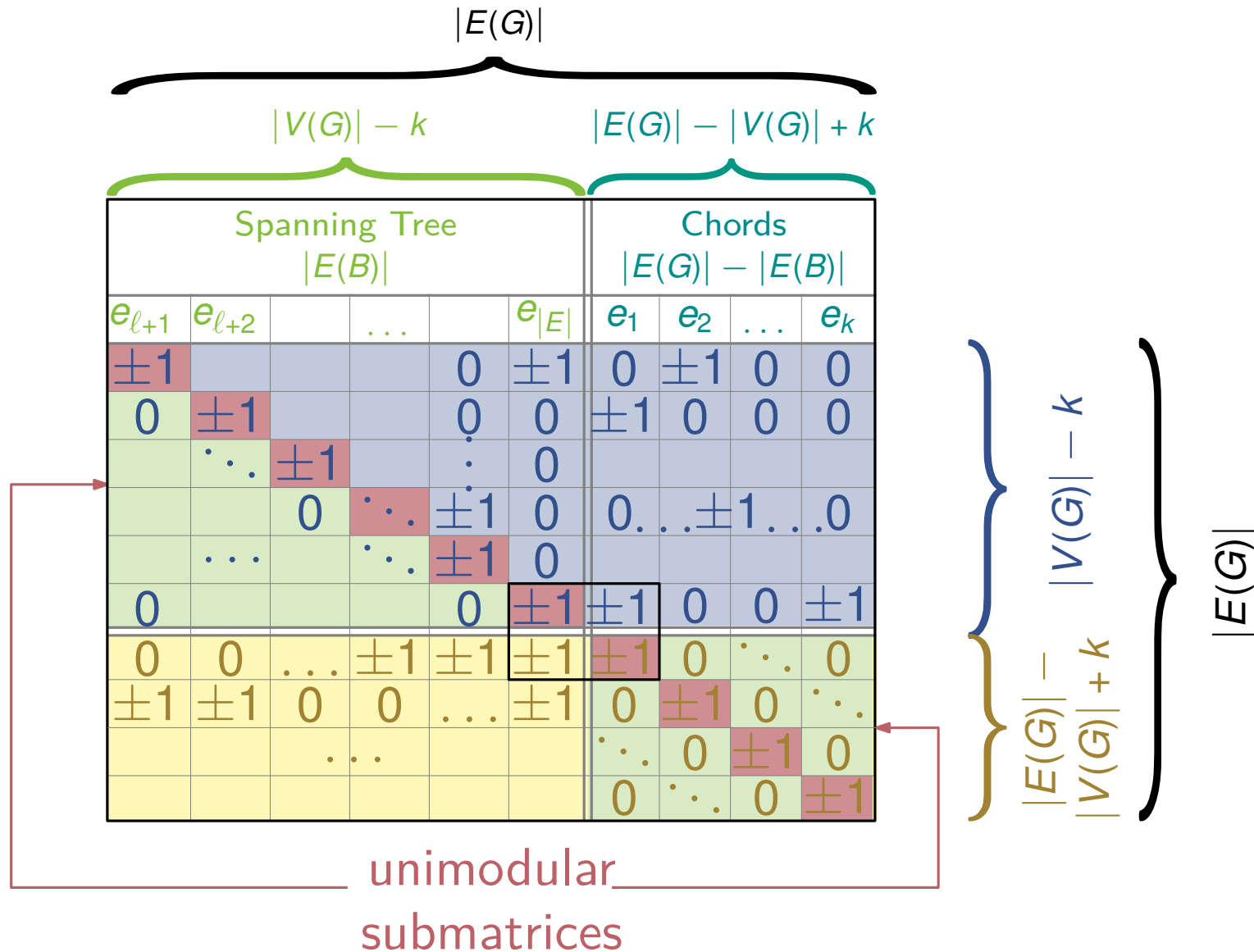
# Structure of the Incidence and Circuit Matrix

7							
5					2		
Spanning Tree					Chords		
	<i>g</i>	<i>e</i>	<i>d</i>	<i>b</i>	<i>a</i>	<i>f</i>	<i>c</i>
3	-1	0	0	1	0	0	-1
4	1	-1	0	0	0	1	0
5	0	1	1	0	0	0	0
6	0	0	-1	0	0	0	1
1	0	0	0	-1	-1	0	0
2	0	0	0	0	1	-1	0
$C_1$	-1	0	0	-1	1	1	0
$C_2$	1	1	-1	0	0	0	1

unimodular submatrices



# General Structure



# General Structure



## Lemma 1

The bases of the incidence matrix  $\mathbf{I}$  and the circuit matrix  $\mathbf{B}$  are TUM. However, the whole system of equations to get an electrically feasible flow using the KCL and KVL is **not** TUM.

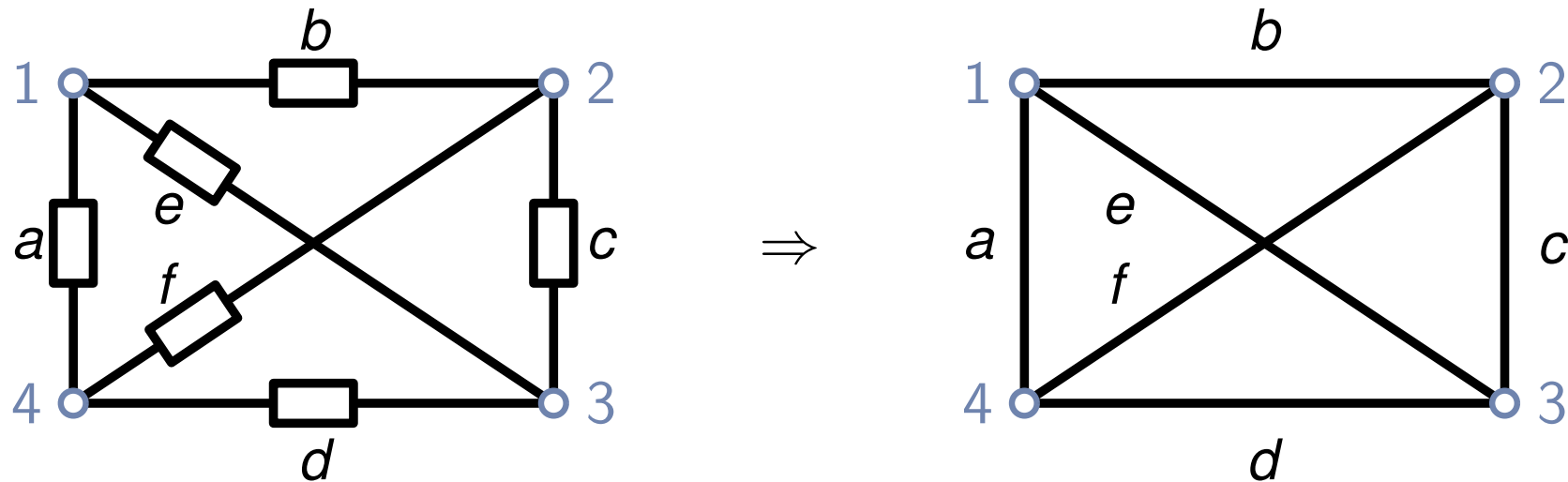
0	0	...	$\pm 1$	$\pm 1$	$\pm 1$	$\pm 1$	0	...	0
$\pm 1$	$\pm 1$	0	0	...	$\pm 1$	0	$\pm 1$	0	...
		...				...	0	$\pm 1$	0
						0	...	0	$\pm 1$

$|E(G)| - |V(G)| + k$

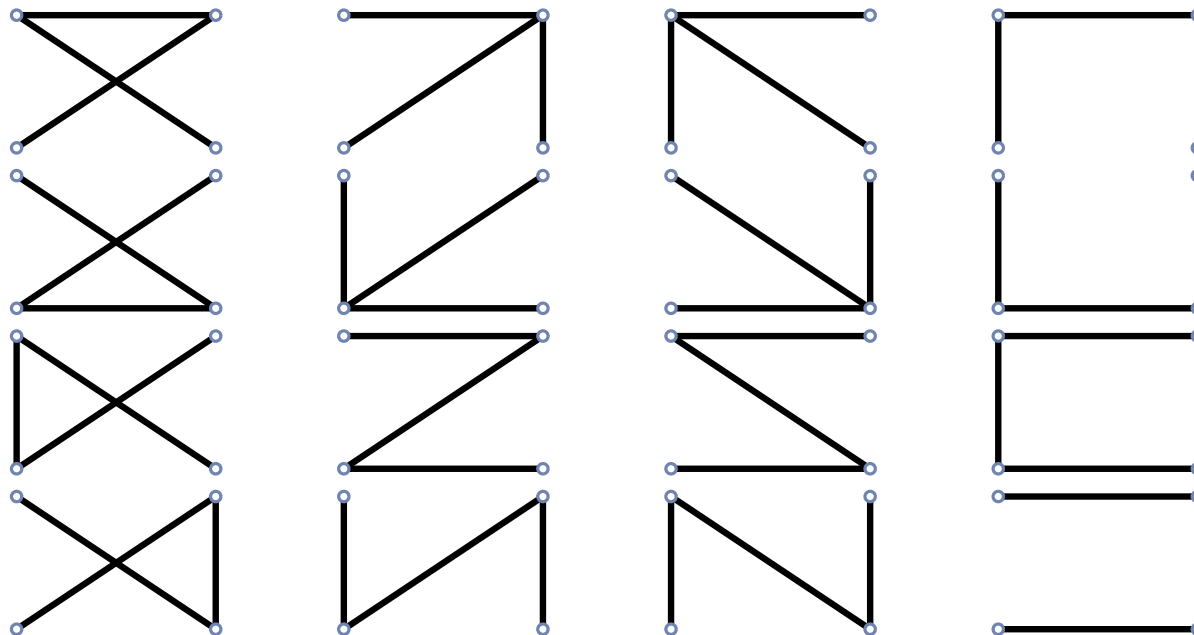
unimodular submatrices



# Circuits and Spanning Trees



All spanning trees  $T$



# An Ancient Algorithm for the Power Flow

- A first algorithm that represents a structural result

## Lemma 2 [p.36, Lemma 1; Shapiro, 1987]

Let every edge of  $G$  have a resistor of 1 ohm. Let  $N$  denote the number of spanning trees and let  $N(s, a \rightarrow b, t)$  be the spanning trees that contain the edge  $(a, b)$  in that particular direction. Put a 1-ampere current between  $s$  and  $t$  and let  $i(a, b) = (N(s, a \rightarrow b, t) - N(s, b \rightarrow a, t)) / N$ . Then  $i(a, b)$  is the current in the edge  $ab$  oriented from  $a$  to  $b$ .

- Apply Binet-Cauchy theorem on matrix  $\mathbf{Y}_n = \mathbf{I} \mathbf{Y}_e \mathbf{I}^T$
- $\Delta_n = \det(\mathbf{Y}_n) = \det(\mathbf{I} \mathbf{Y}_n \mathbf{I}^T) = \sum_{T \in \mathcal{T}} (\text{Tree-Admittance Product of } T)$
- Tree-Admittance Product  $\sum_{(u,w) \in E(T)} \mathbf{Y}_{u,w}$

## Theorem 3 [p.522, Theorem 23; Whitney, 1935]

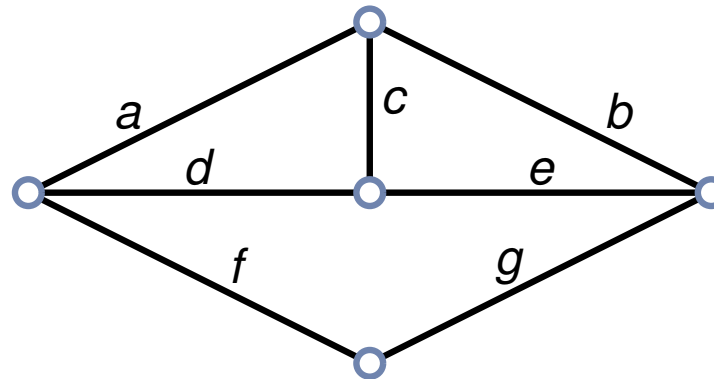
Let  $\mathcal{E}$  be a planar embedding of a primal graph  $G$  with  $G(\mathcal{E})$  being isomorphic to  $G$ . The graphs  $G$  and  $G^*$  are duals if and only if there is a bijection  $\mu_{\text{dual}}: E(G) \rightarrow E(G^*)$  between their edges such that bases in one correspond to base complements in the other.

# Primal and Dual Graphs

## Theorem 3 [p.522, Theorem 23; Whitney, 1935]

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primal graph  $G$

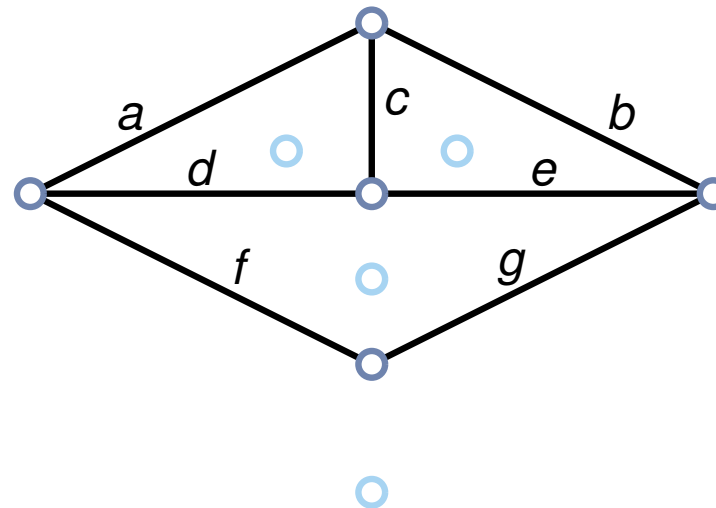


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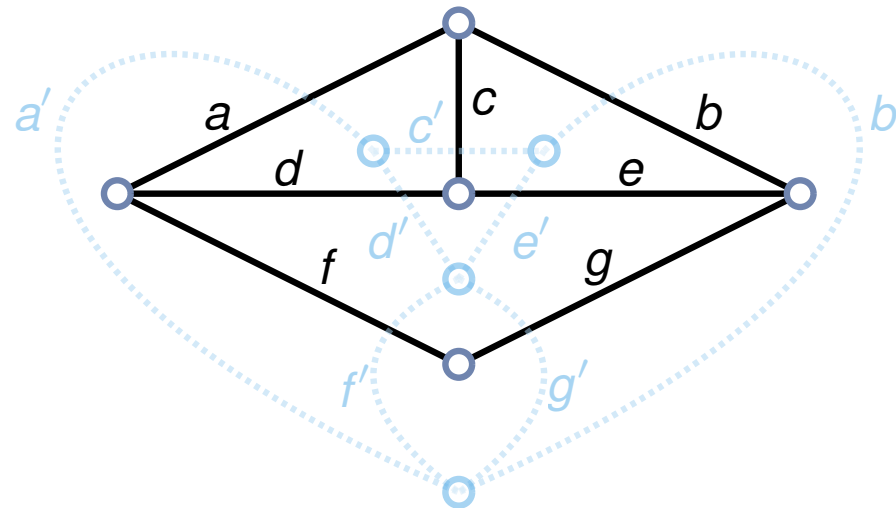
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dual graph  $G^*$



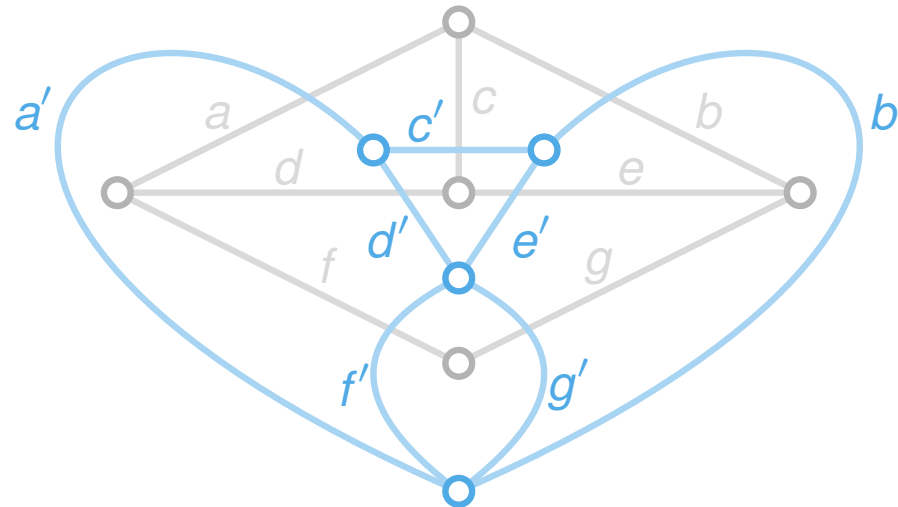
# Primal and Dual Graphs

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# Primal and Dual Graphs

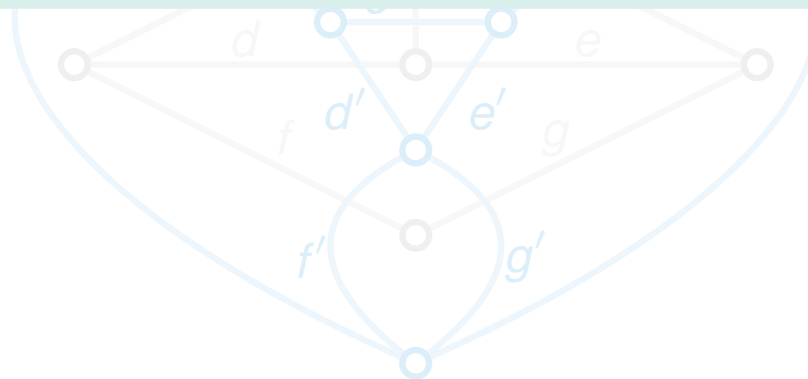
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## Corollary 4 [p.85, Corollary 4-24; Seshu and Reed, 1961]

If  $G$  and  $G^*$  are dual graphs, the incidence matrix of either graphs is a circuit matrix of the other (with the proper rank, and each row representing a cycle); that is

$$I_1 = B_2 \text{ and } I_2 = B_1.$$





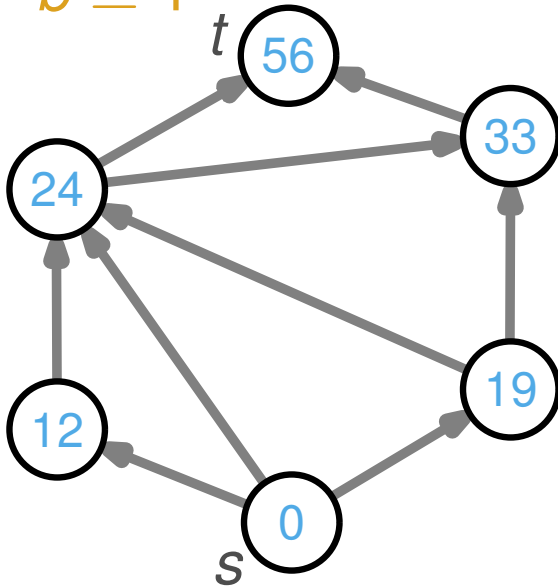
## PLANAR $s$ - $t$ PF AND MPF

**Instance:** A plane  $s$ - $t$ -graph  $G$ , its dual graph  $G^*$  and a bijection  $\mu_{\text{dual}}: E(G) \rightarrow E(G^*)$ .

**Objective:** Find feasible flows  $f_G, f_{G^*}: E \rightarrow \mathbb{R}_{\geq 0}$  in  $G$  and  $G^*$  such that for every edge  $e \in E(G)$  we have

$$f_G(e) = f_{G^*}(\mu_{\text{dual}}(e)) \cdot b(e).$$

$b \equiv 1$

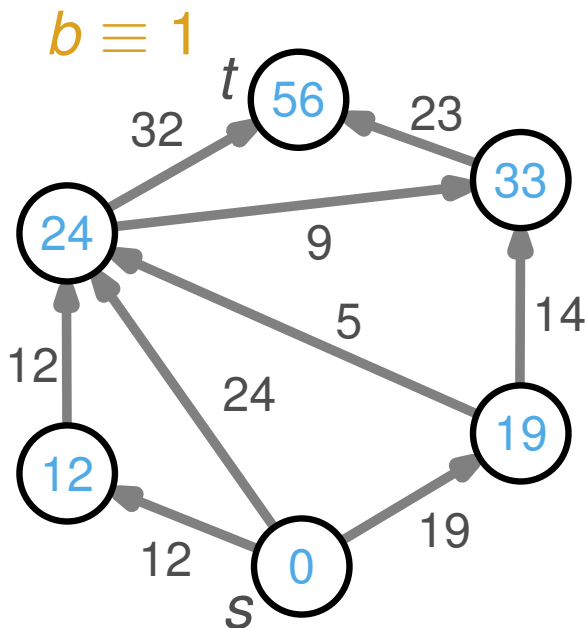


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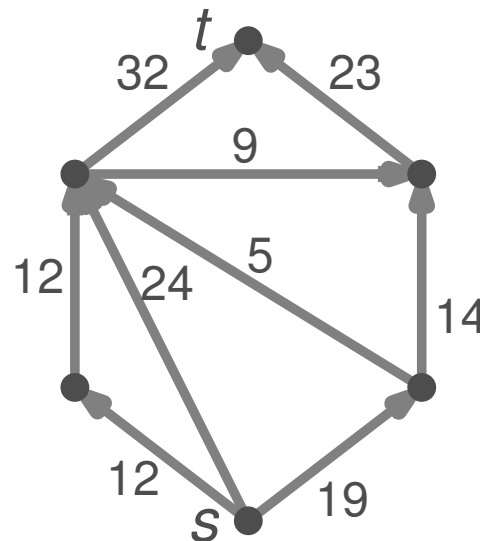
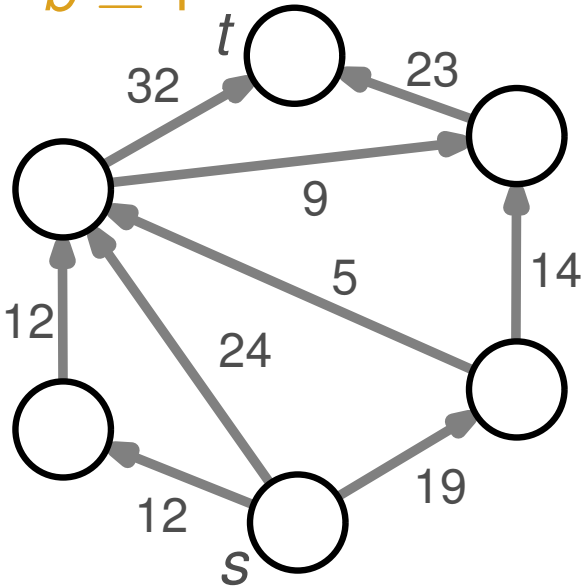
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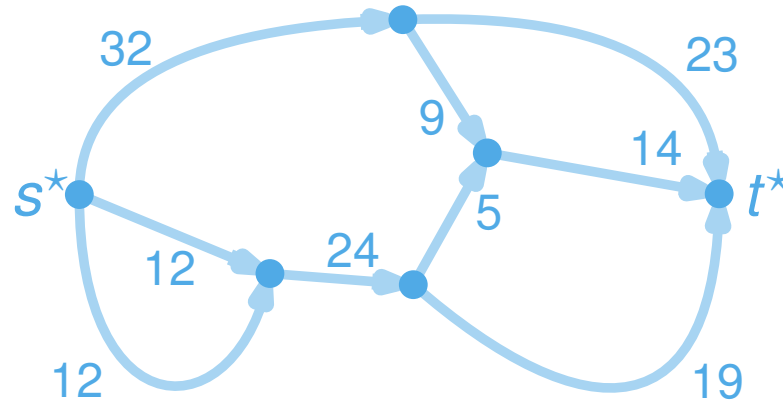
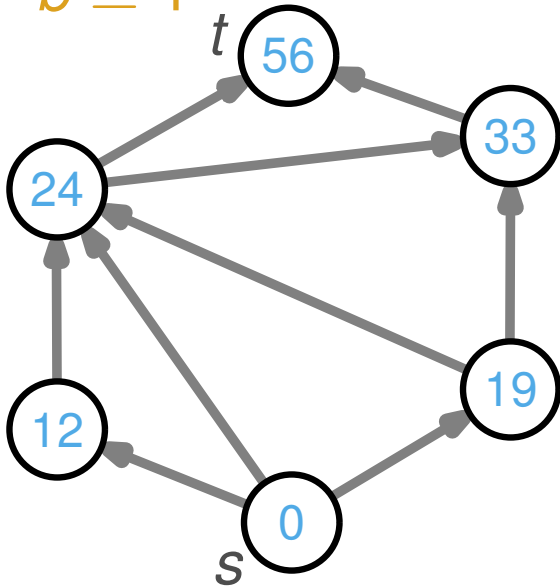
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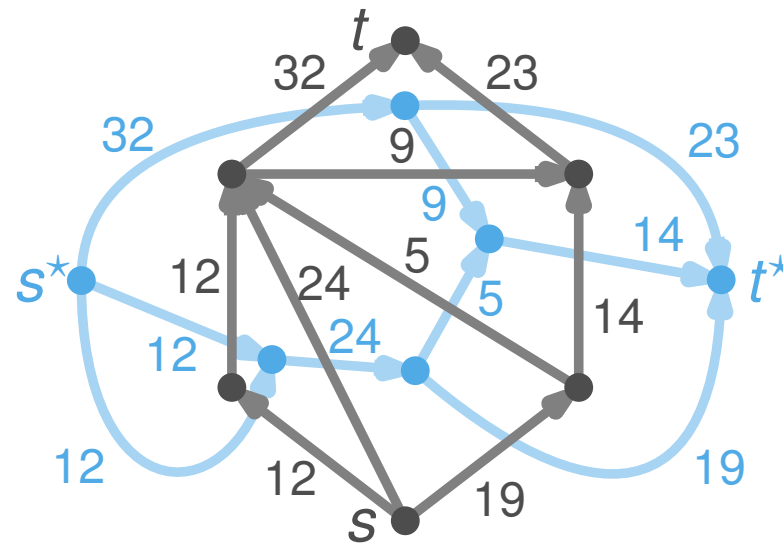
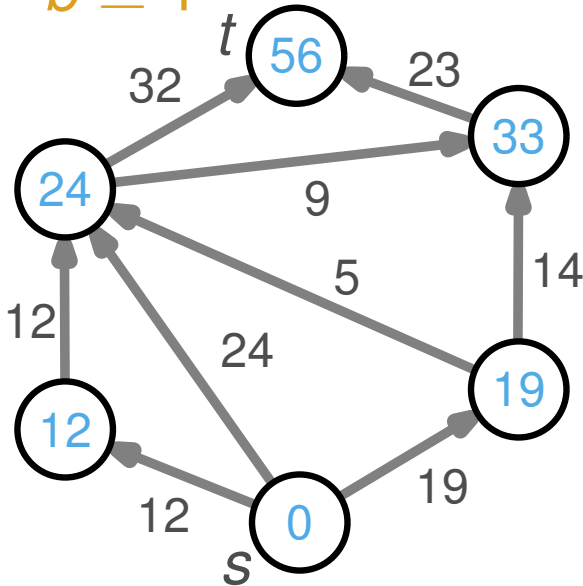
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# Power Flow Problem Reformulation

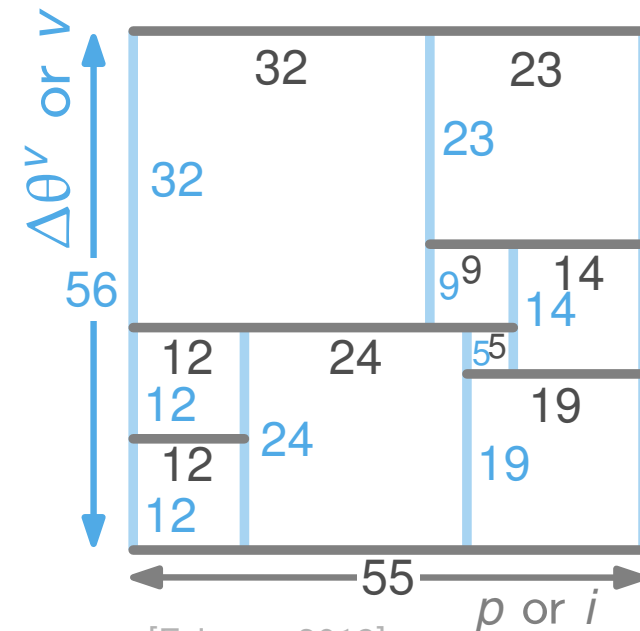
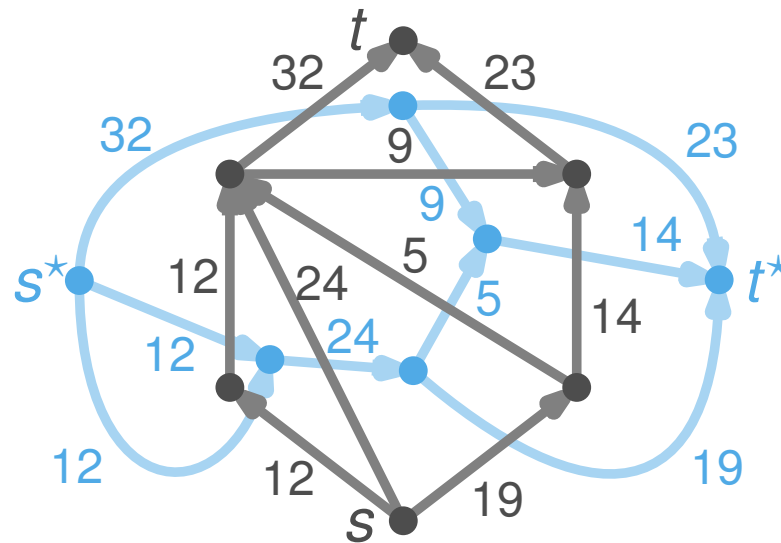
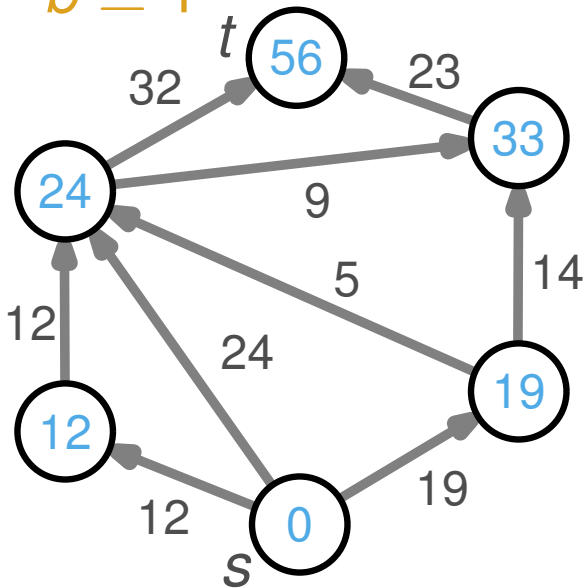
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[Felsner, 2013]

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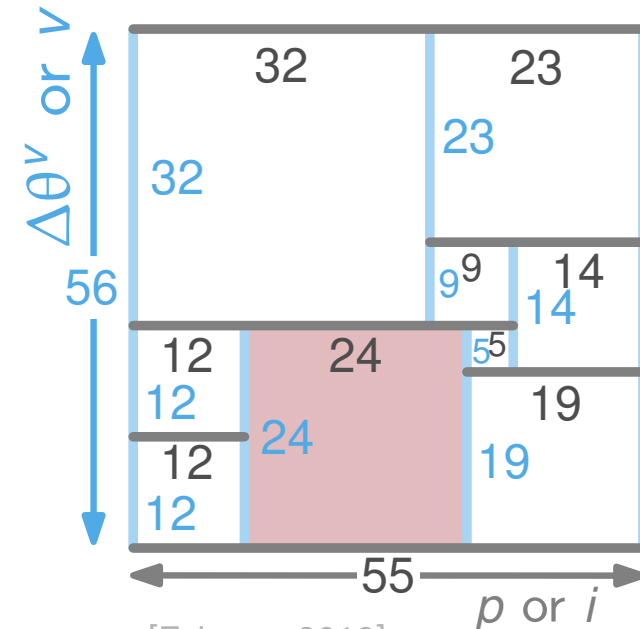
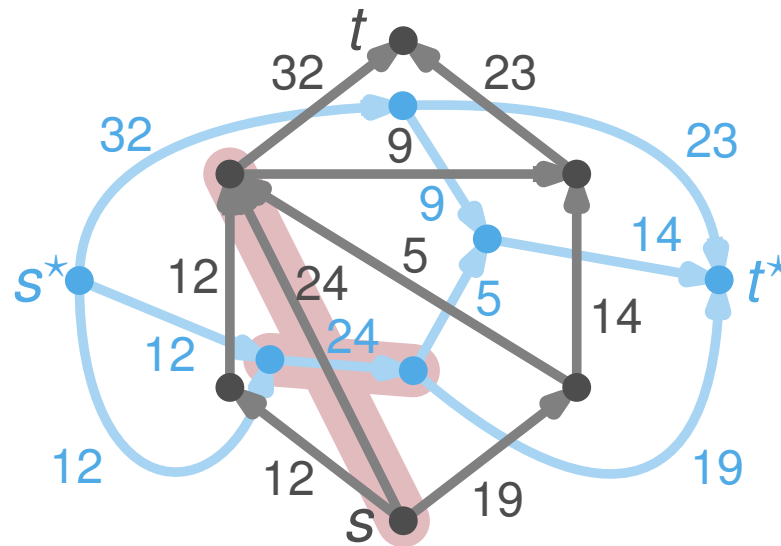
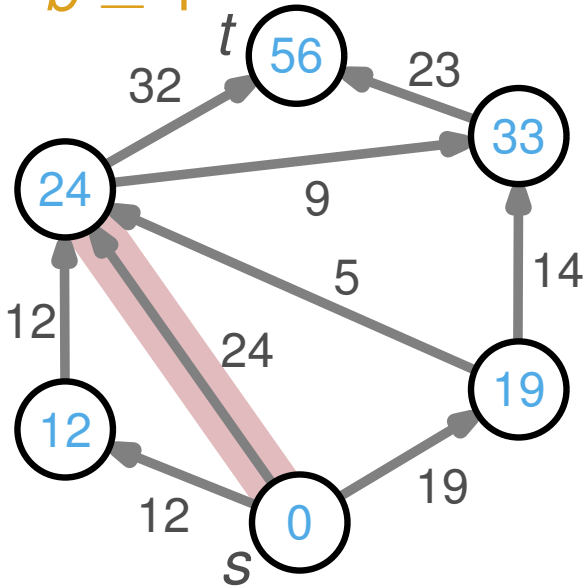
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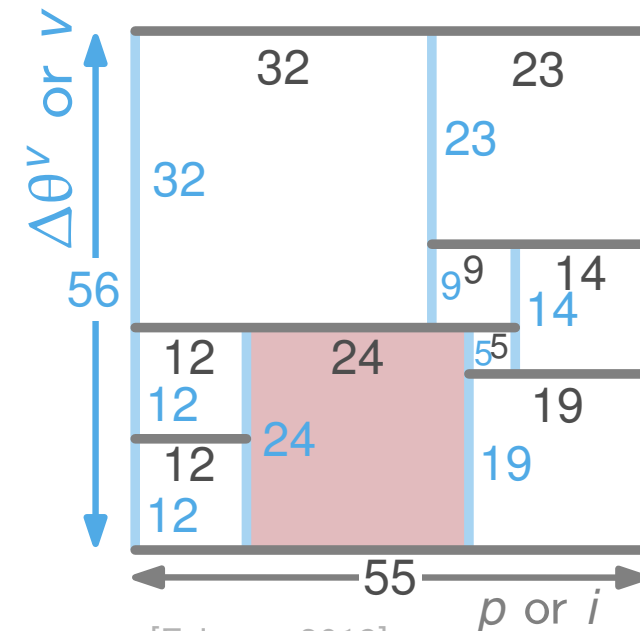
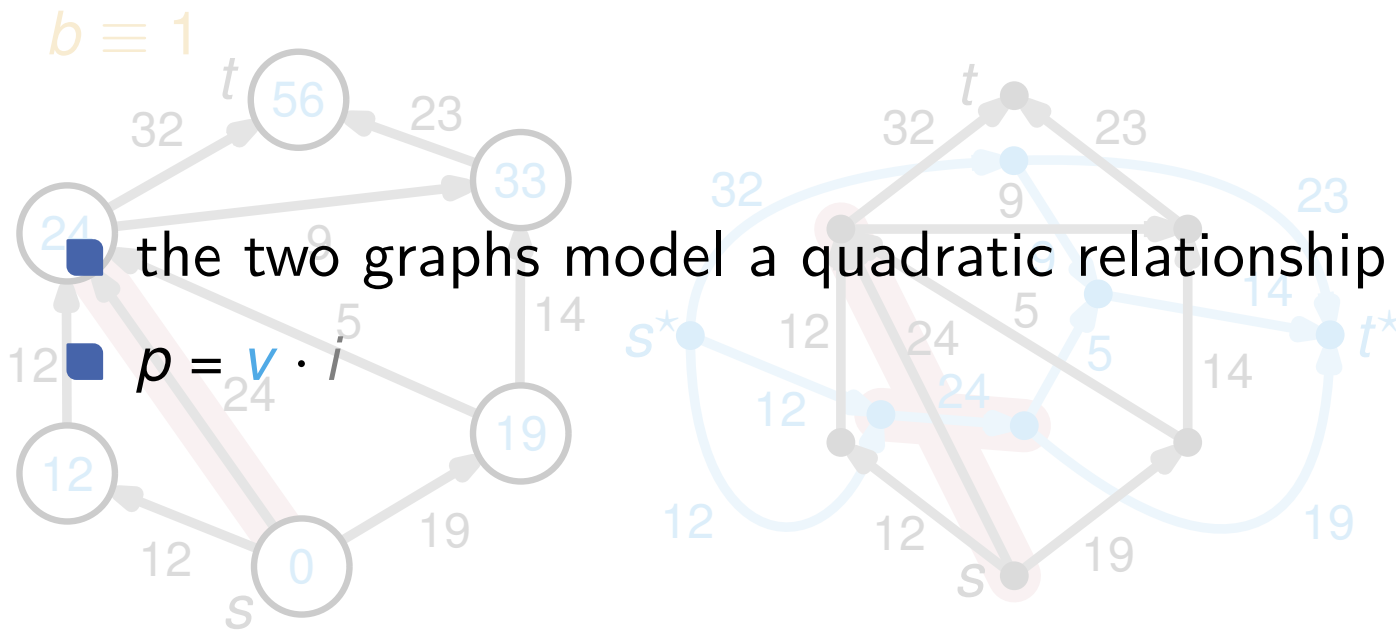
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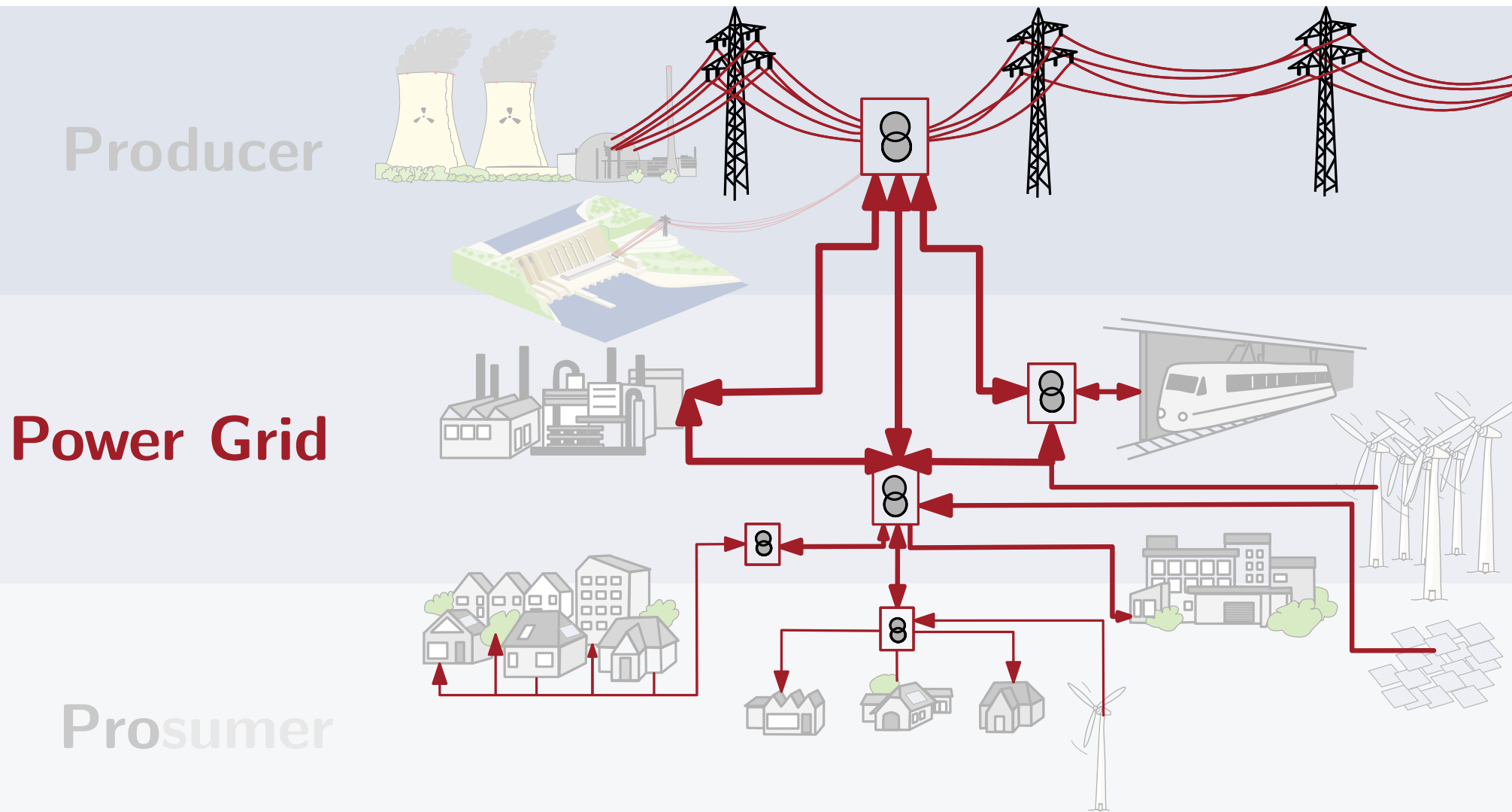
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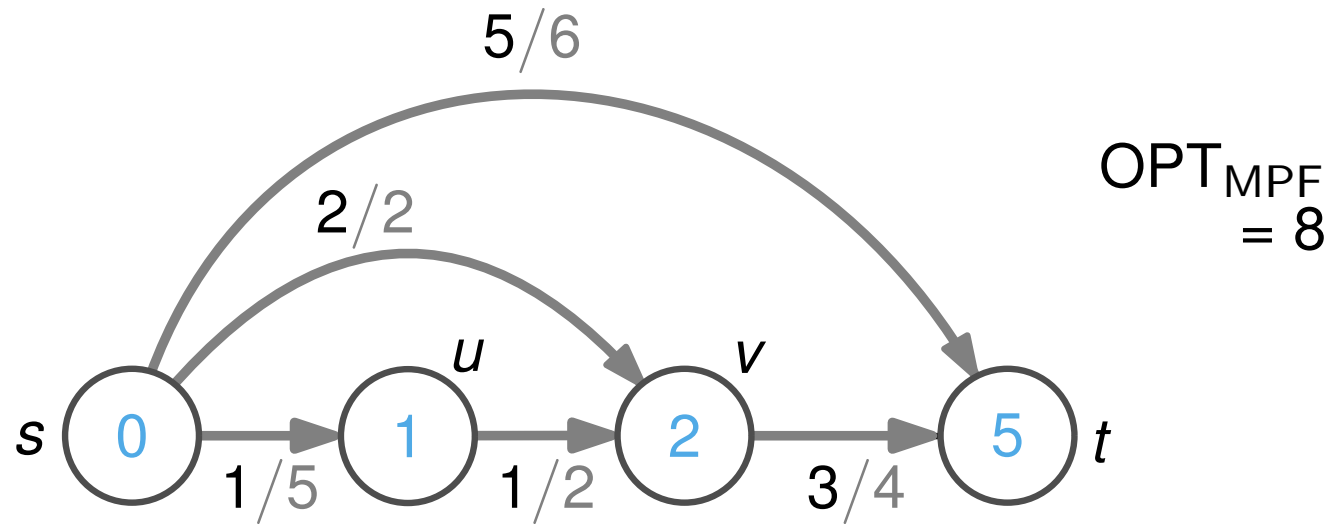
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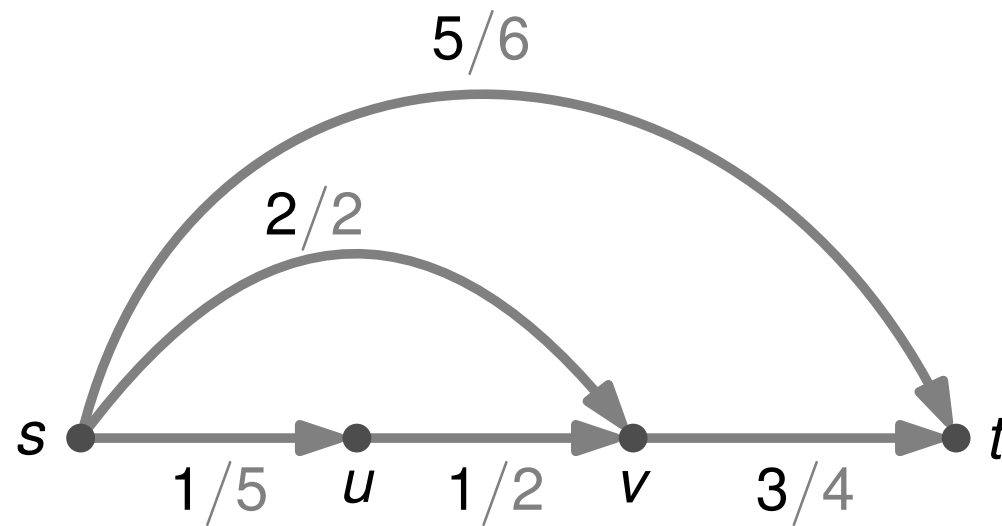
# Towards an Algorithm for the Power Flow



# Prisoner's Dilemma



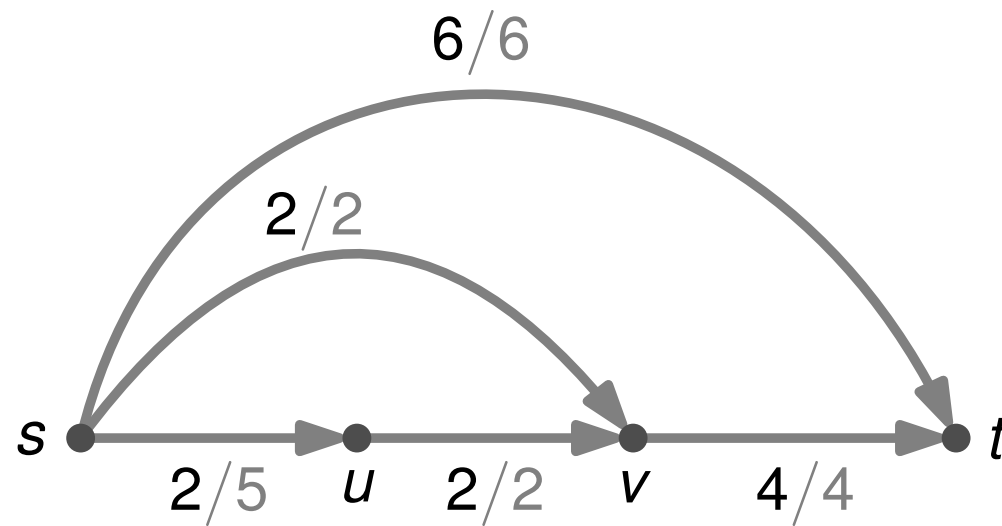
# Prisoner's Dilemma



$$\text{OPT}_{\text{MPF}} = 8$$

# Prisoner's Dilemma

Prisoner 1

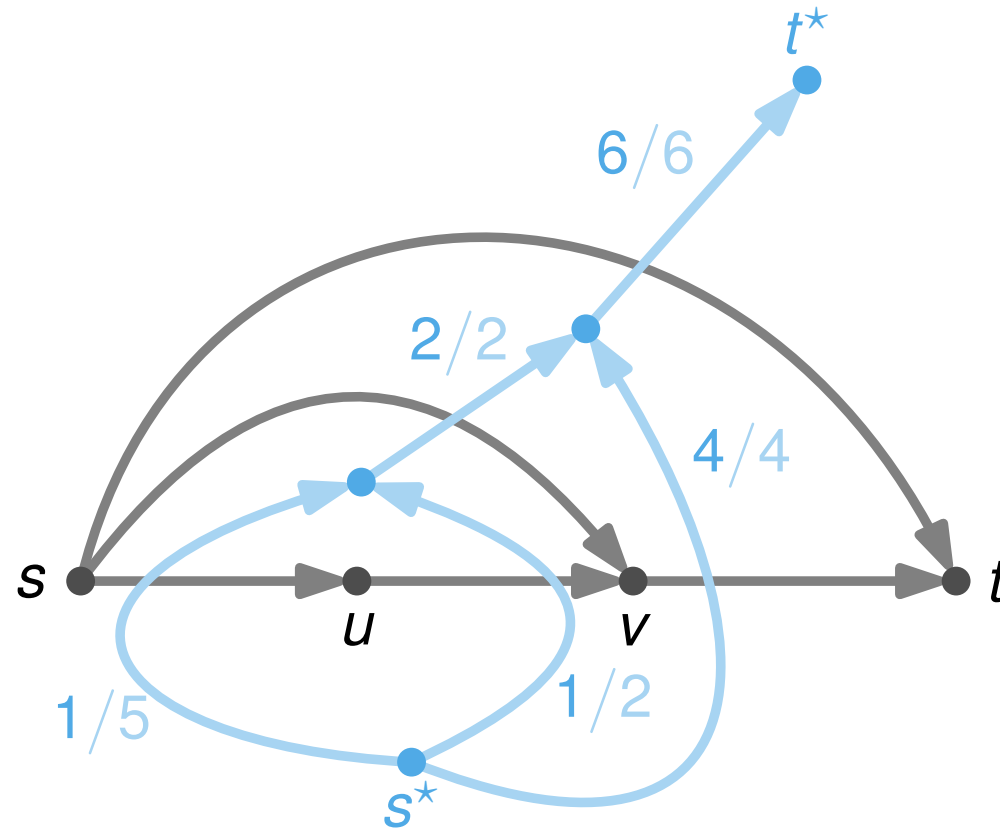


$$\text{OPT}_{\text{MF}} = 10$$

# Prisoner's Dilemma

Prisoner 1

Prisoner 2

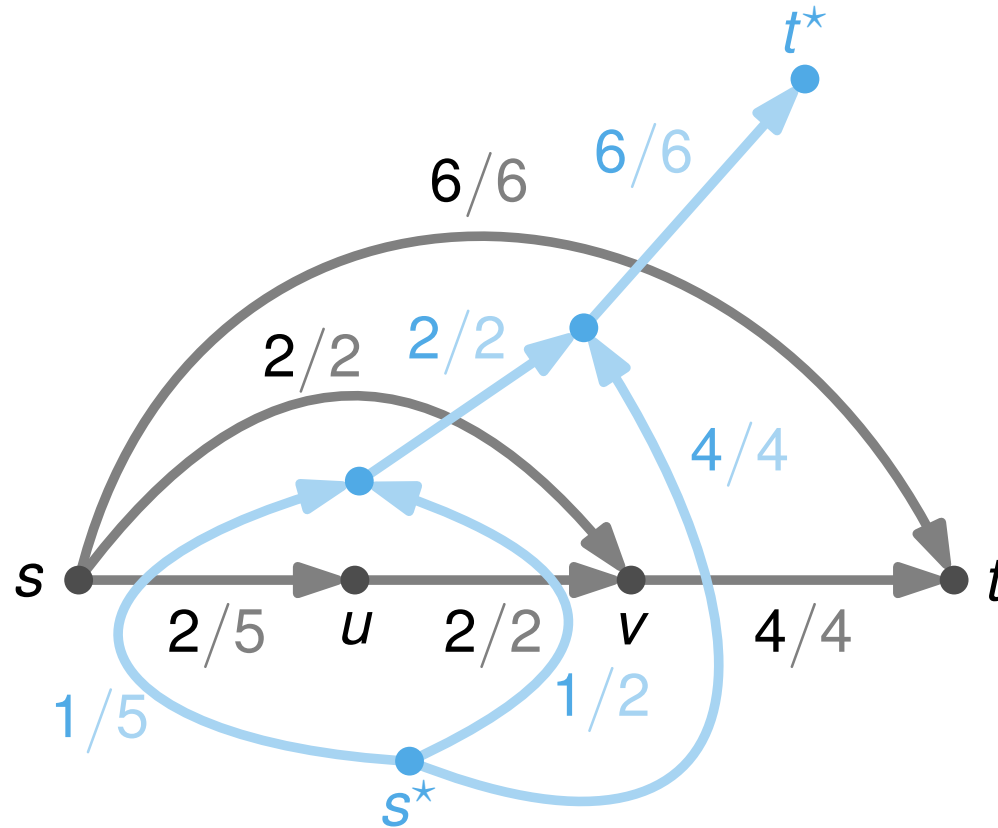


$$\text{OPT}_{\text{MF}} = 6$$

# Prisoner's Dilemma

Prisoner 1

Prisoner 2



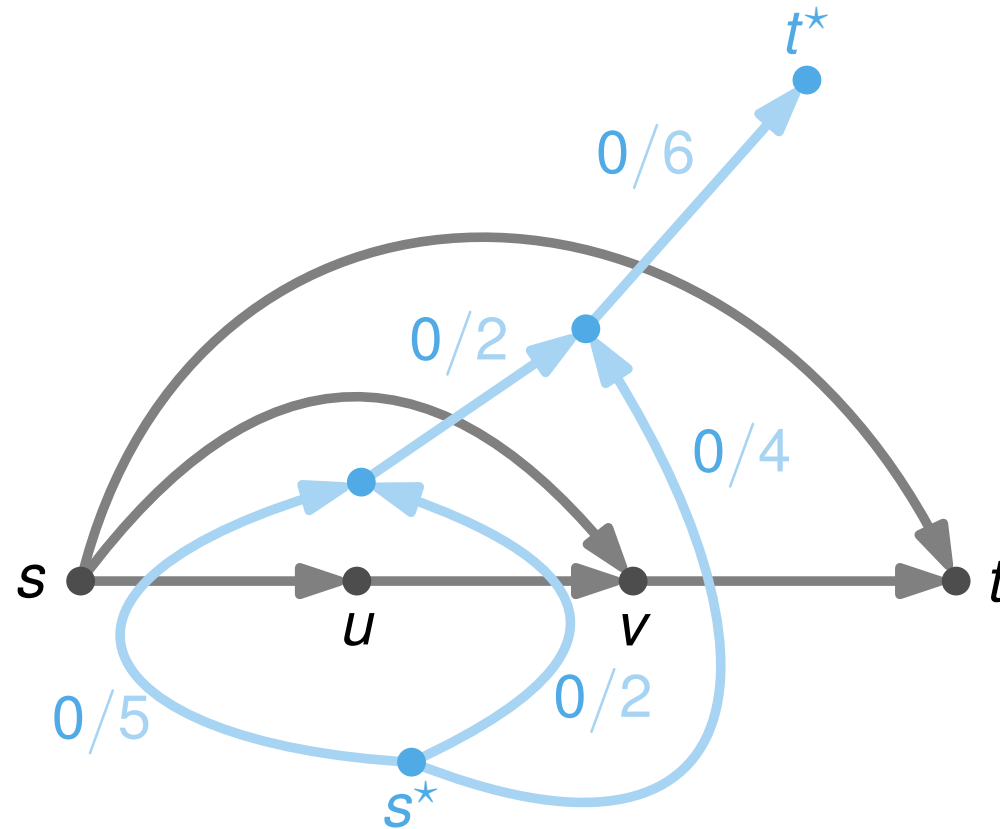
$$\text{OPT}_{\text{MF}} = 6$$

$$\text{OPT}_{\text{MF}} = 10$$

# Prisoner's Dilemma

Prisoner 1

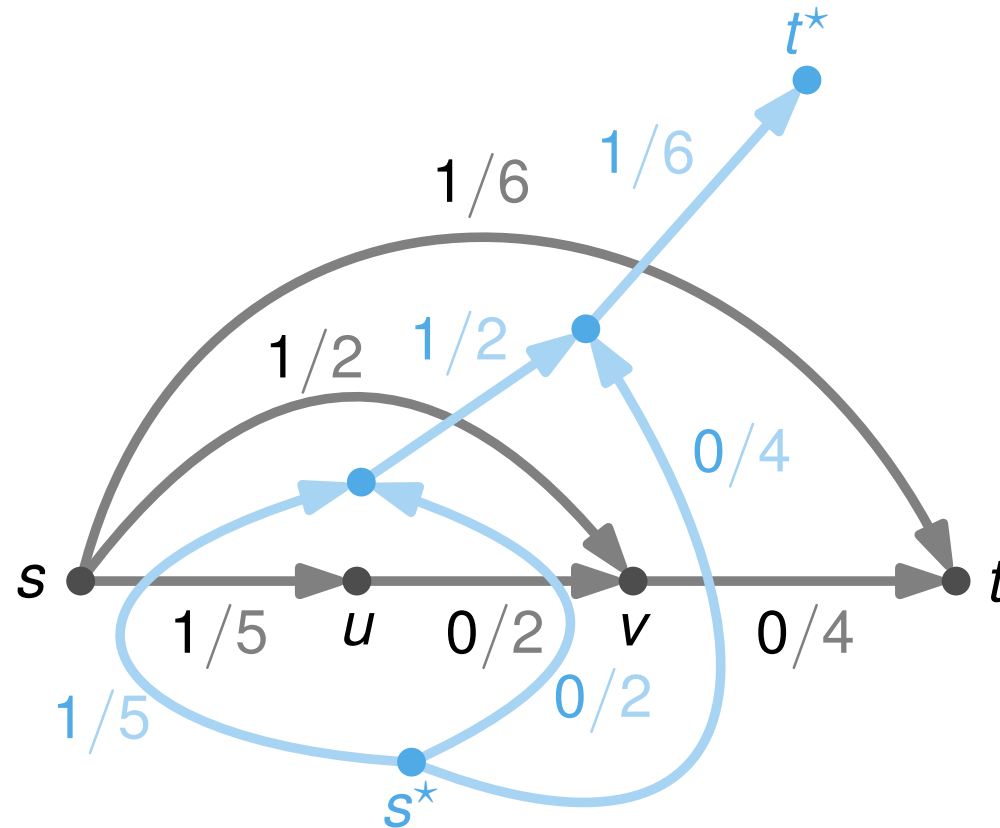
Prisoner 2



# Prisoner's Dilemma

Prisoner 1

Prisoner 2

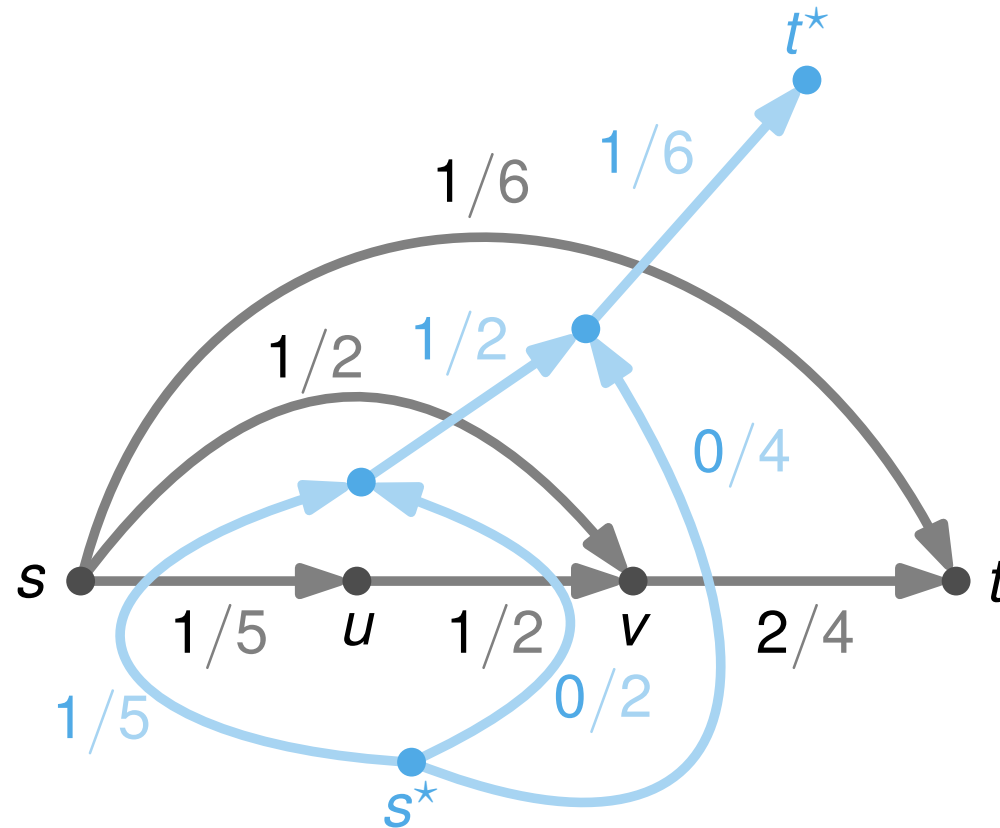




# Prisoner's Dilemma

Prisoner 1

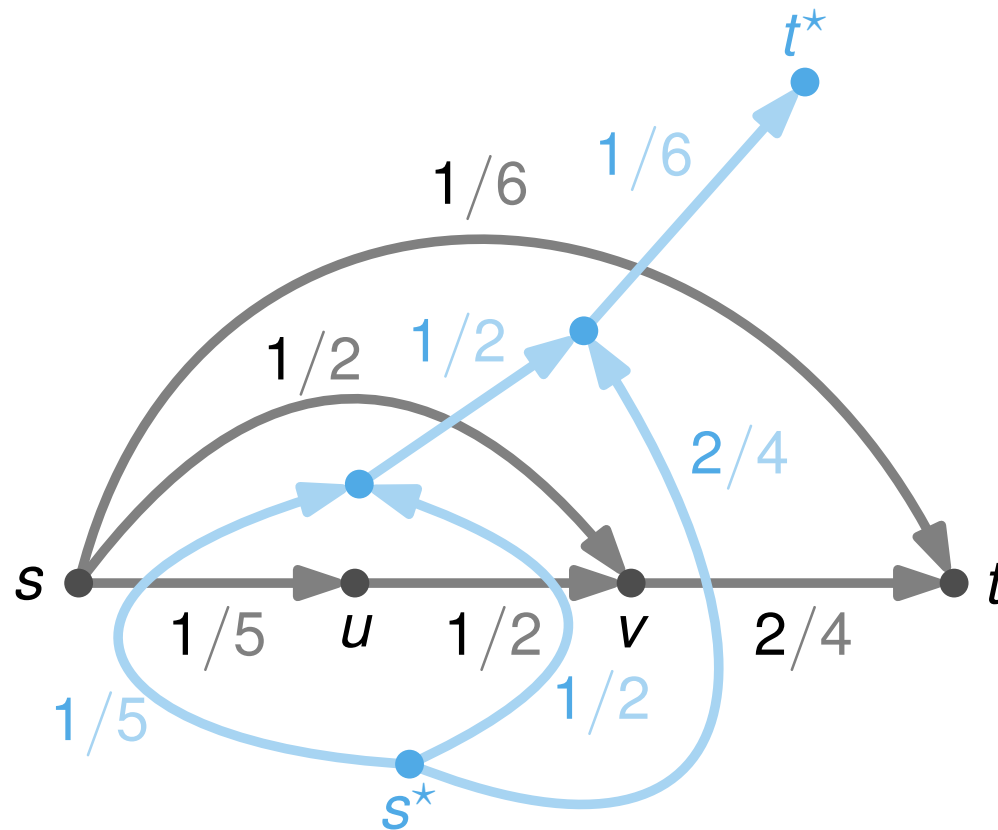
Prisoner 2



# Prisoner's Dilemma

Prisoner 1

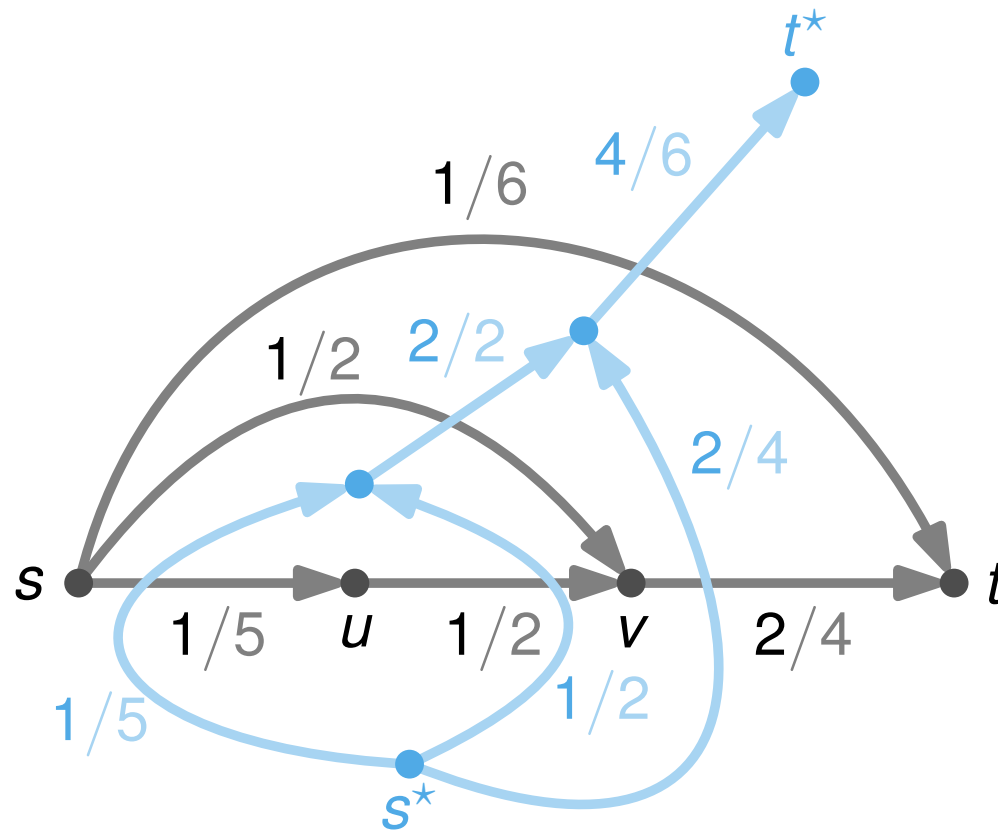
Prisoner 2



# Prisoner's Dilemma

Prisoner 1

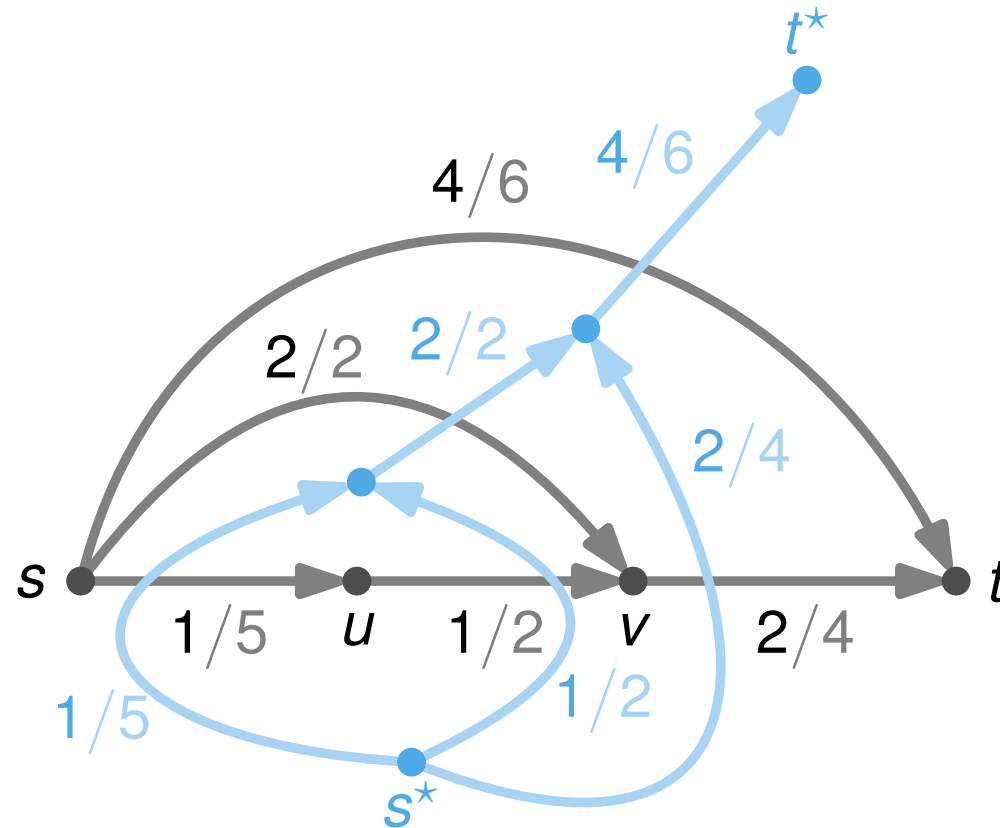
Prisoner 2



# Prisoner's Dilemma

Prisoner 1

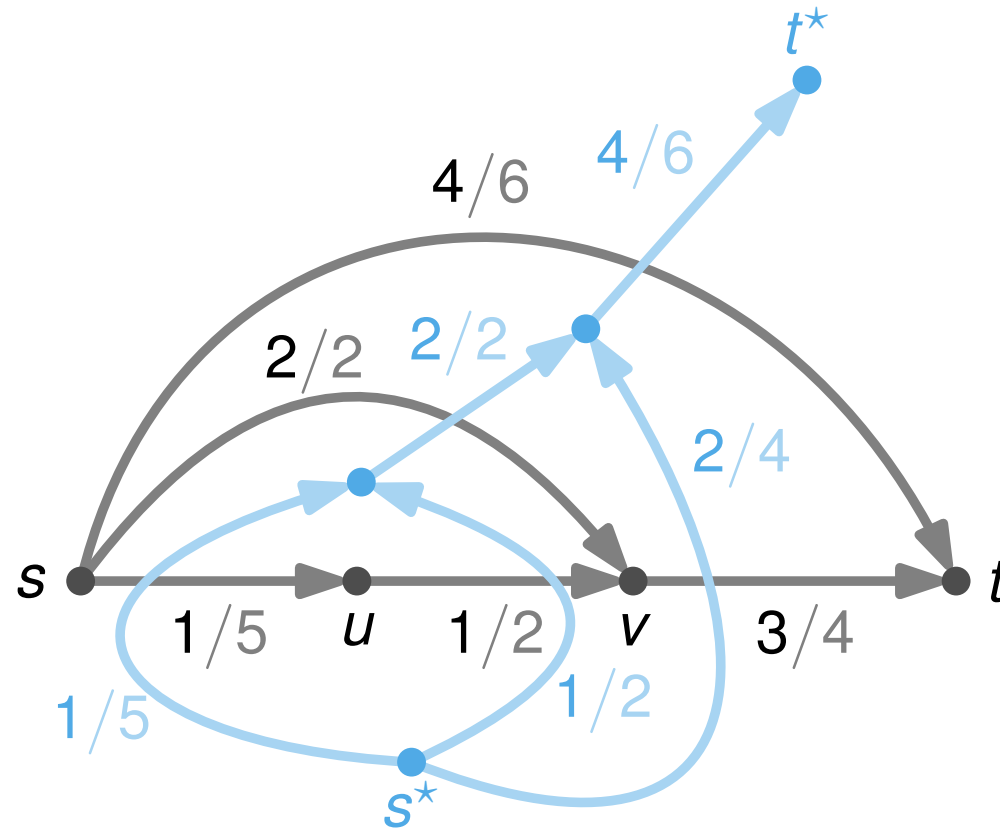
Prisoner 2



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Prisoner 1

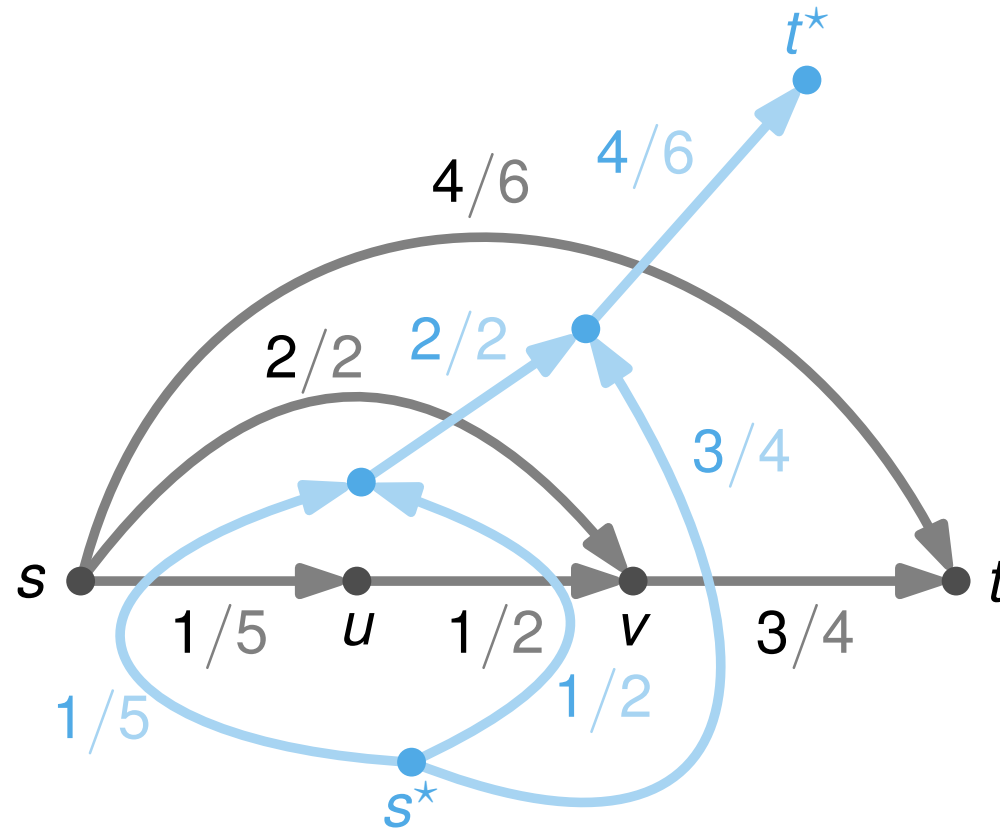
Prisoner 2



# Prisoner's Dilemma

Prisoner 1

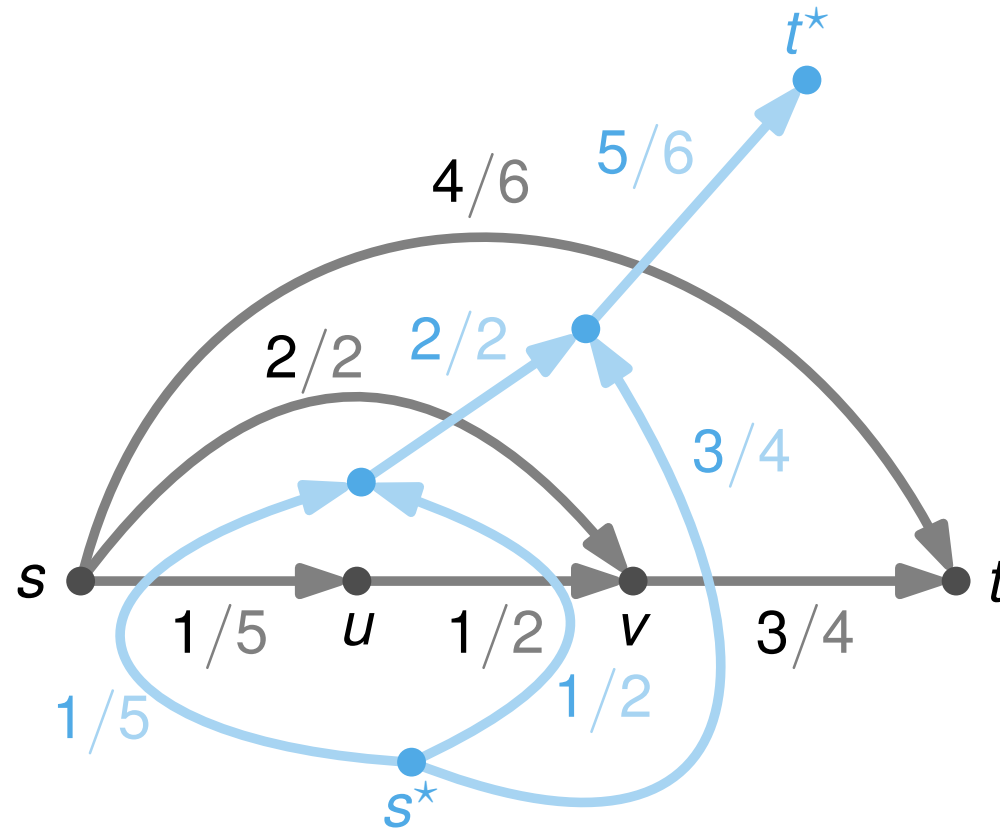
Prisoner 2



# Prisoner's Dilemma

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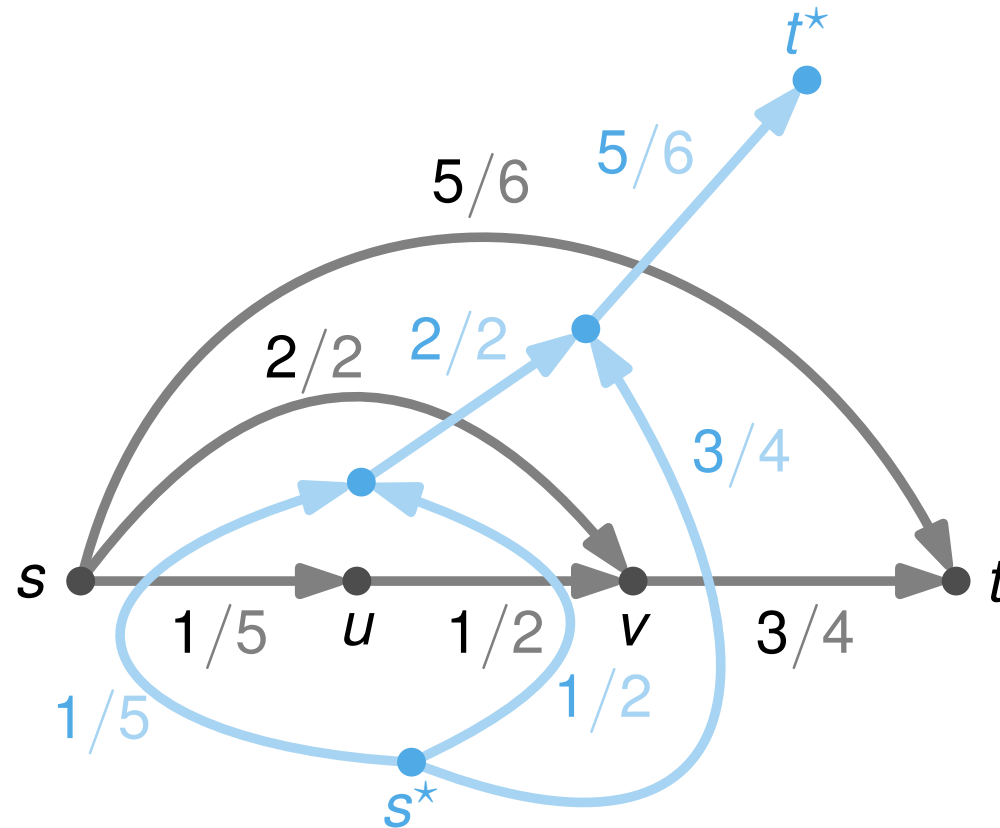
Prisoner 2



# Prisoner's Dilemma

Prisoner 1

Prisoner 2

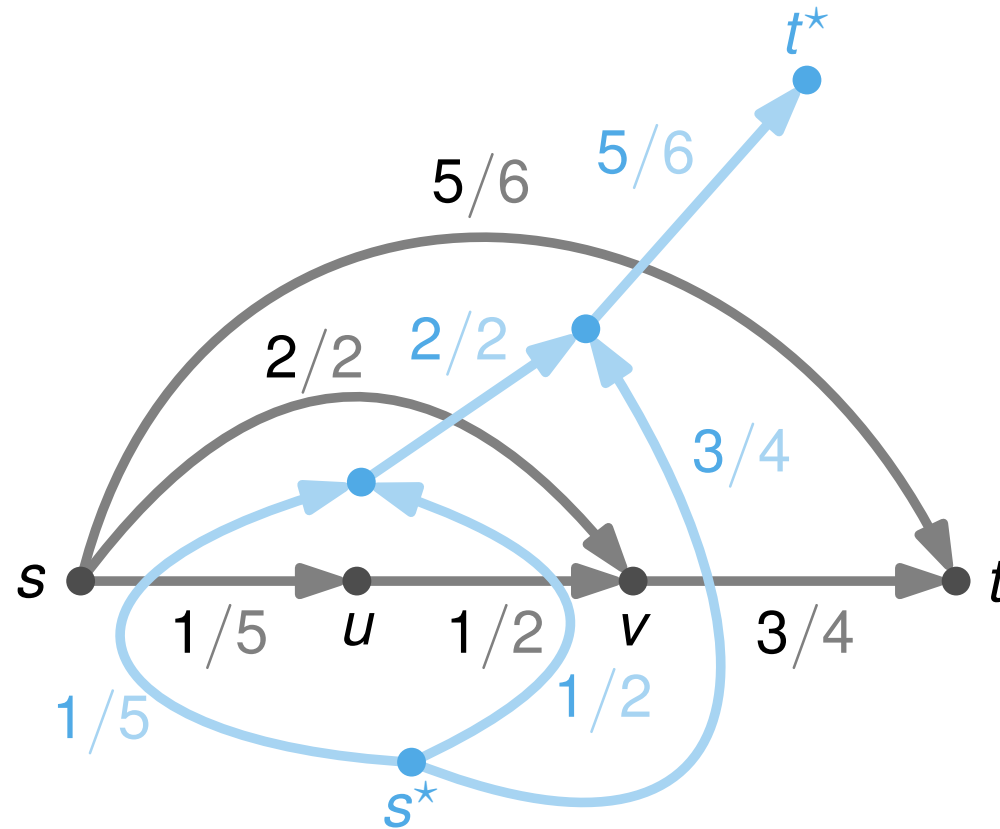




# Prisoner's Dilemma

Prisoner 1

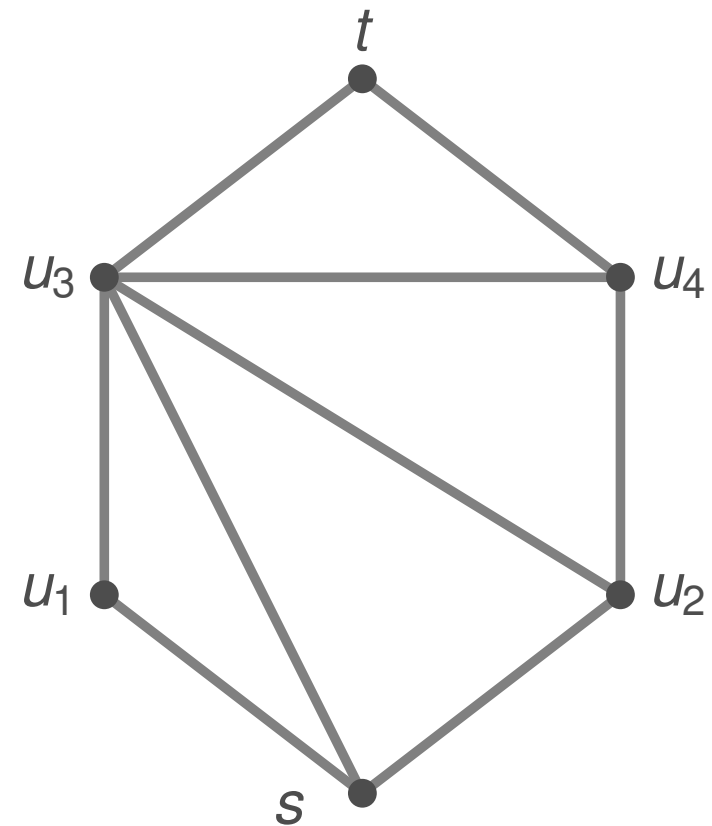
Prisoner 2



$$\text{OPT}_{\text{MPF}} = 5$$

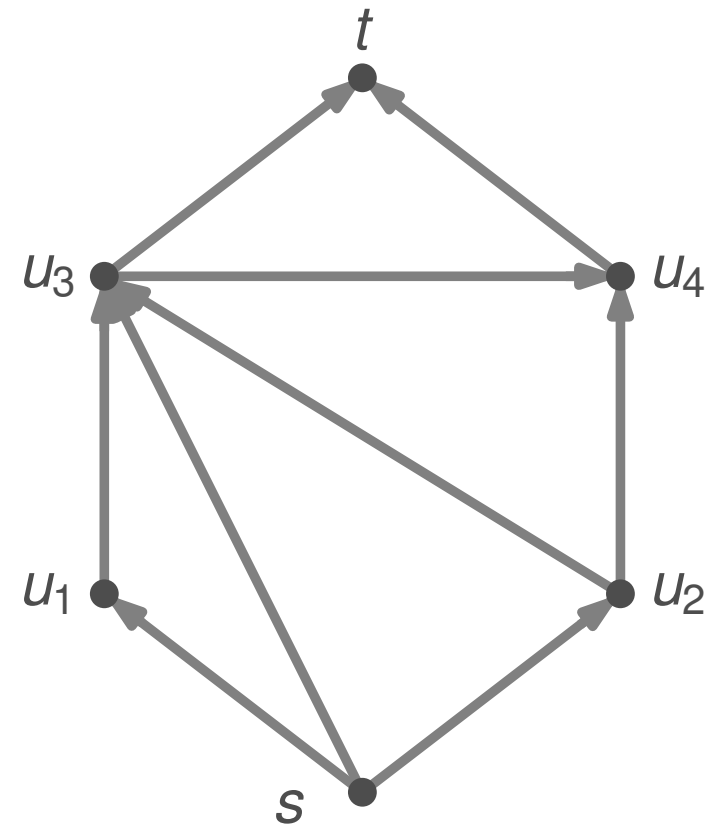
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# Algorithmic Sketch



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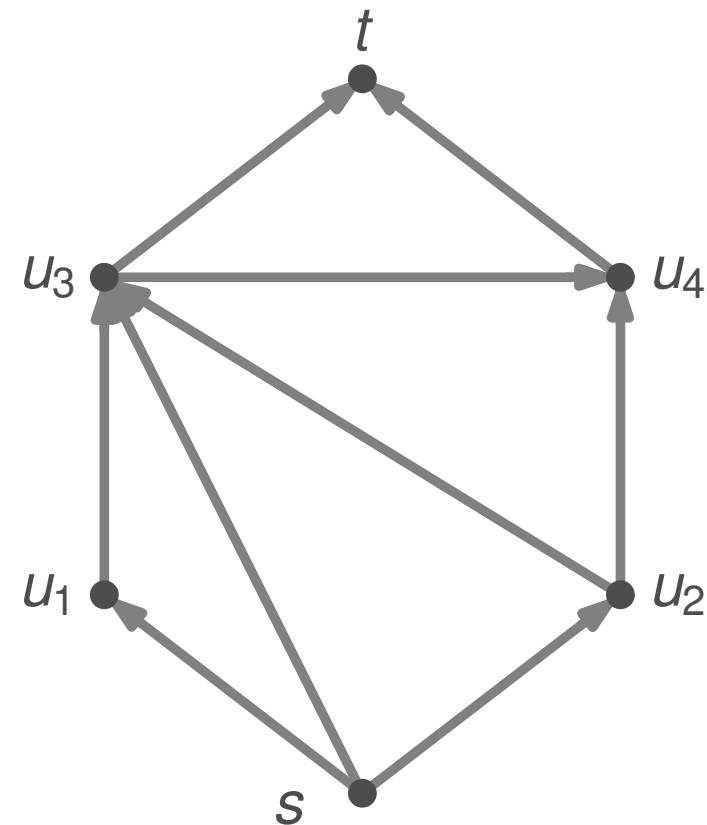
$G = \text{bipolarSubgraphOf}(G, s, t)$



# Algorithmic Sketch

$G = \text{bipolarSubgraphOf}(G, s, t)$

$\mathcal{E} = \text{planarEmbeddingOf}(G)$



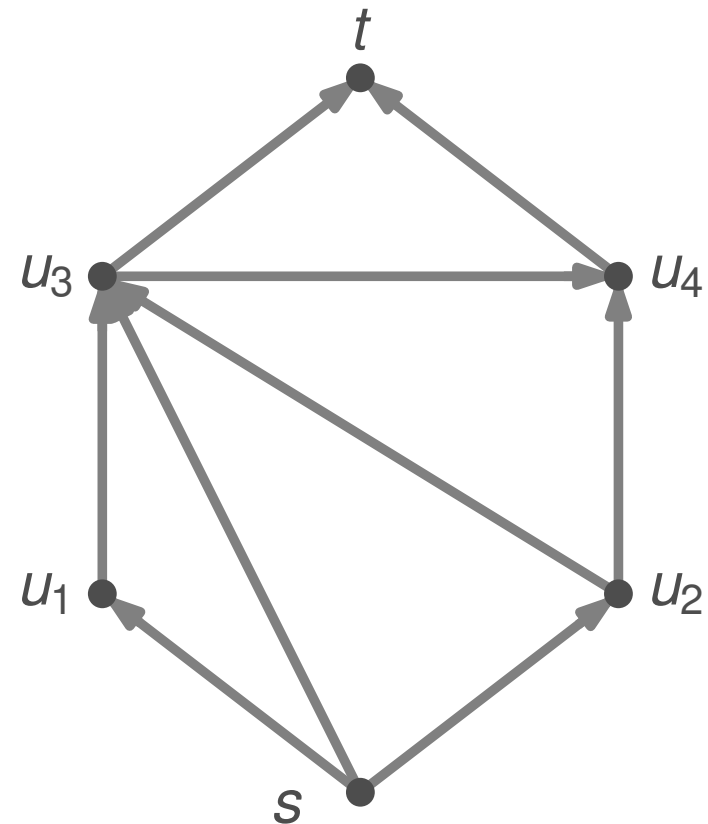
▷ PQ-Tree; Invariant  $G(\mathcal{E}) \cong G$

# Algorithmic Sketch

$G = \text{bipolarSubgraphOf}(G, s, t)$

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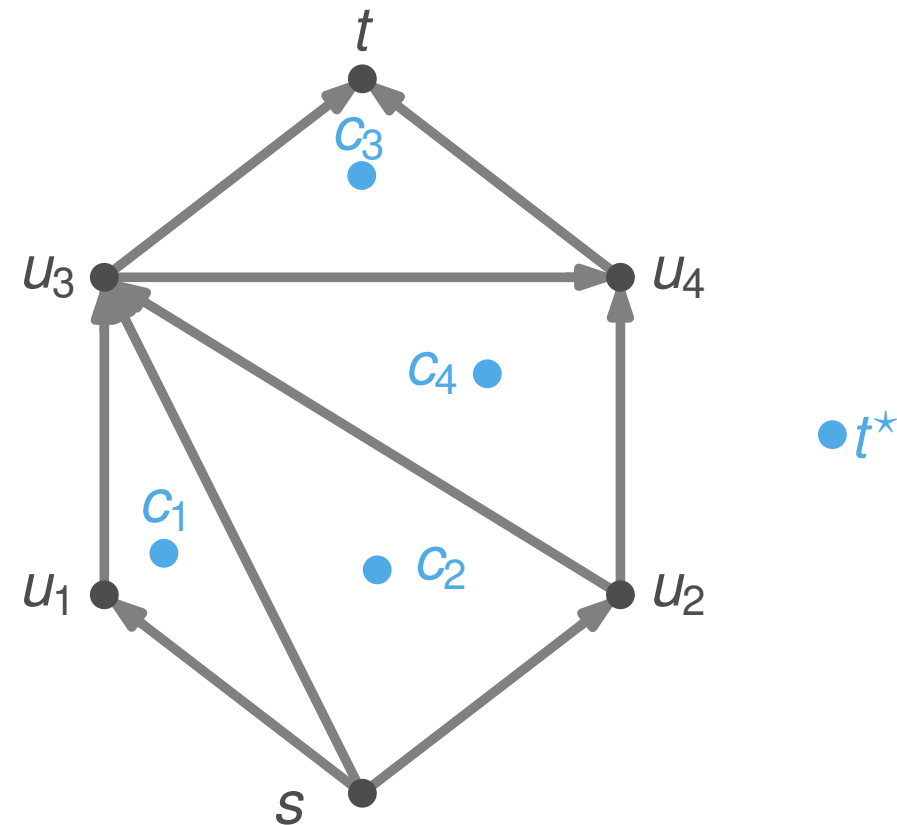


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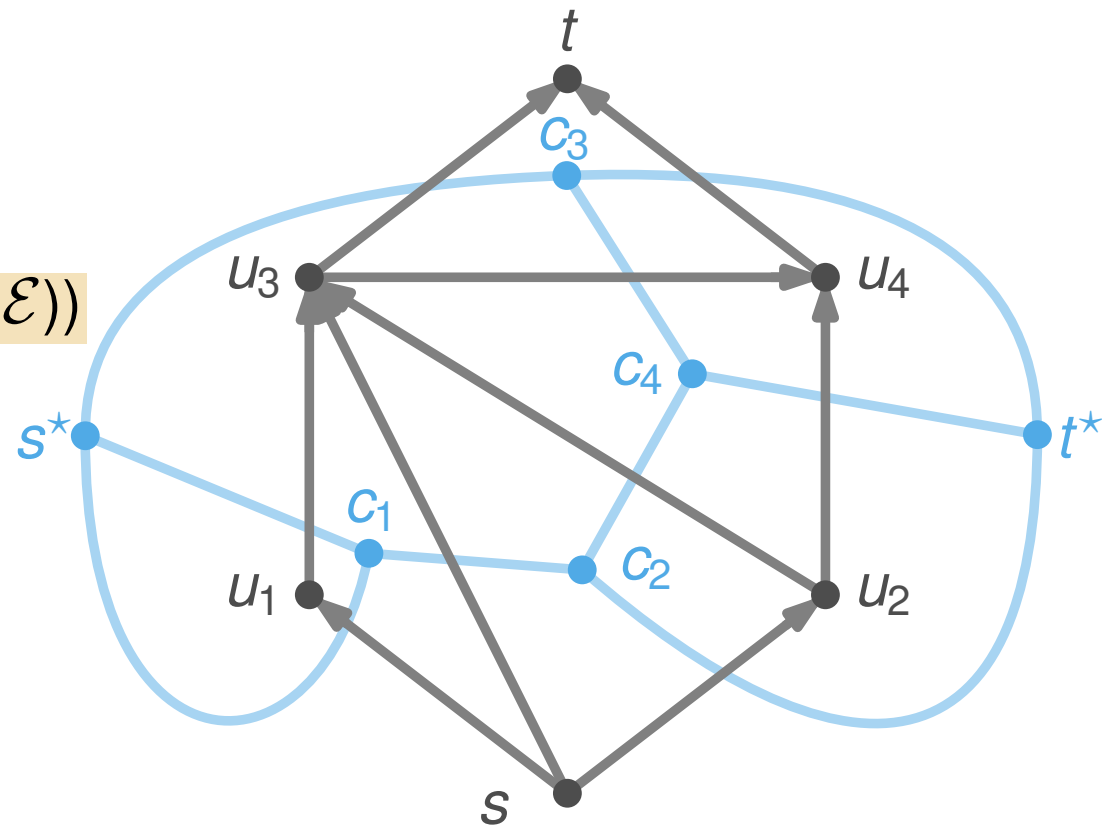


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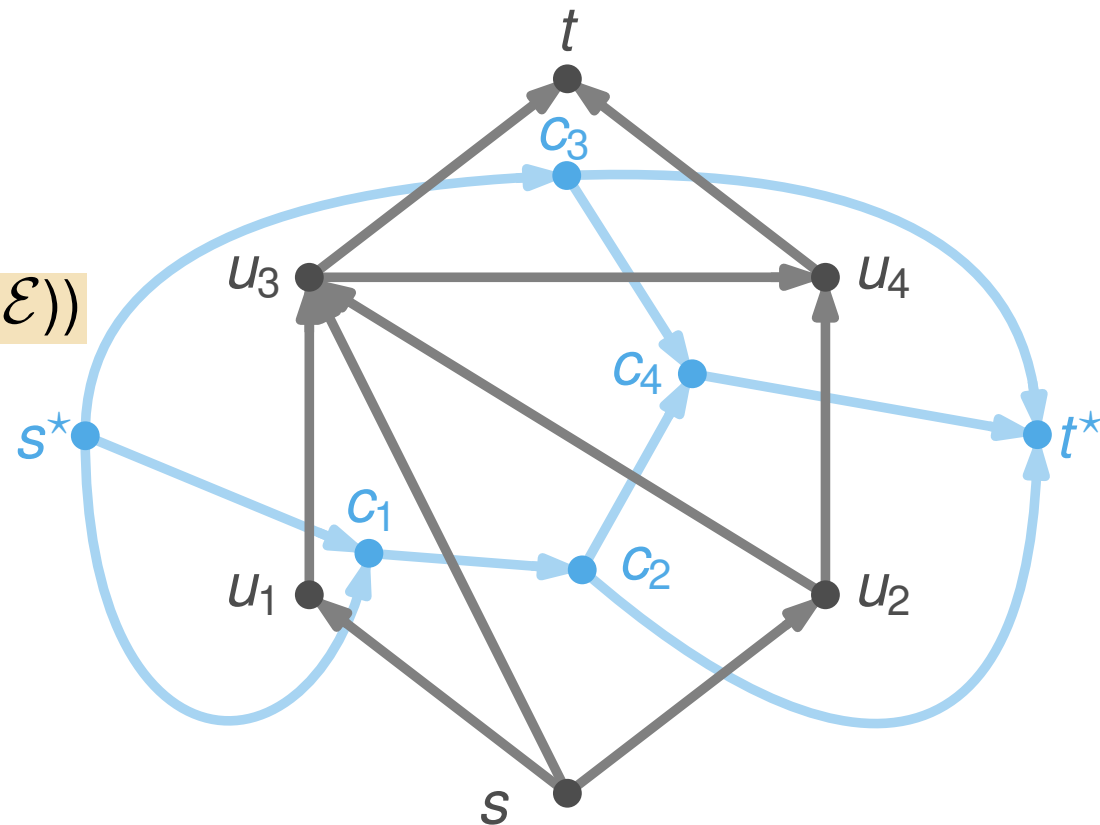


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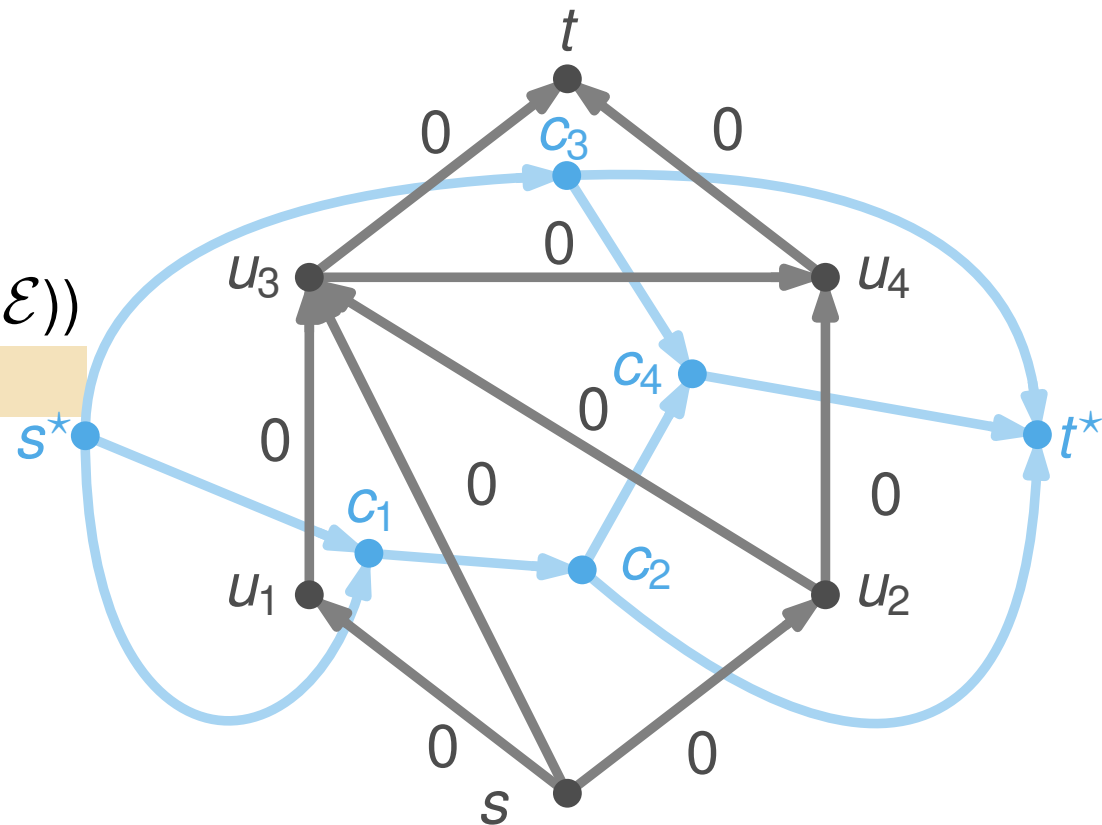
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$f \equiv 0$



▷ Augment flow along an incident edge at source  $s$

# Algorithmic Sketch

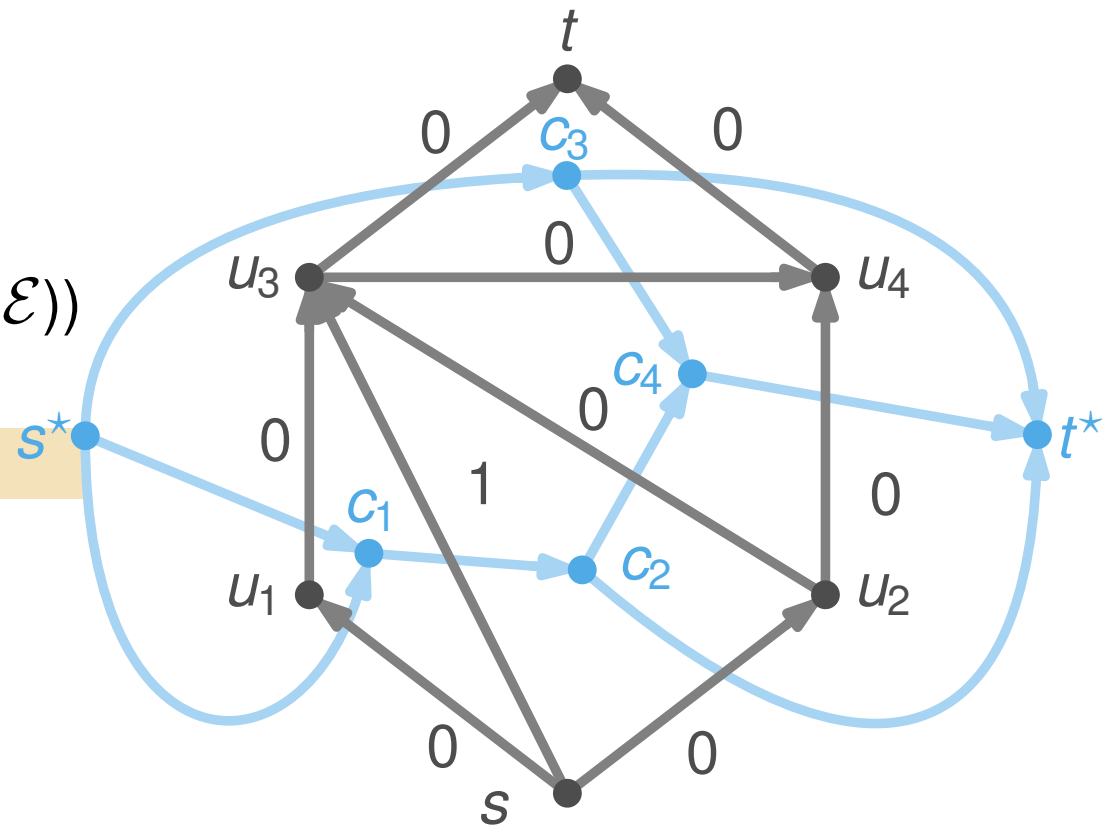
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$f(s, u) = 1$  for some  $u \in V(G)$



# Algorithmic Sketch

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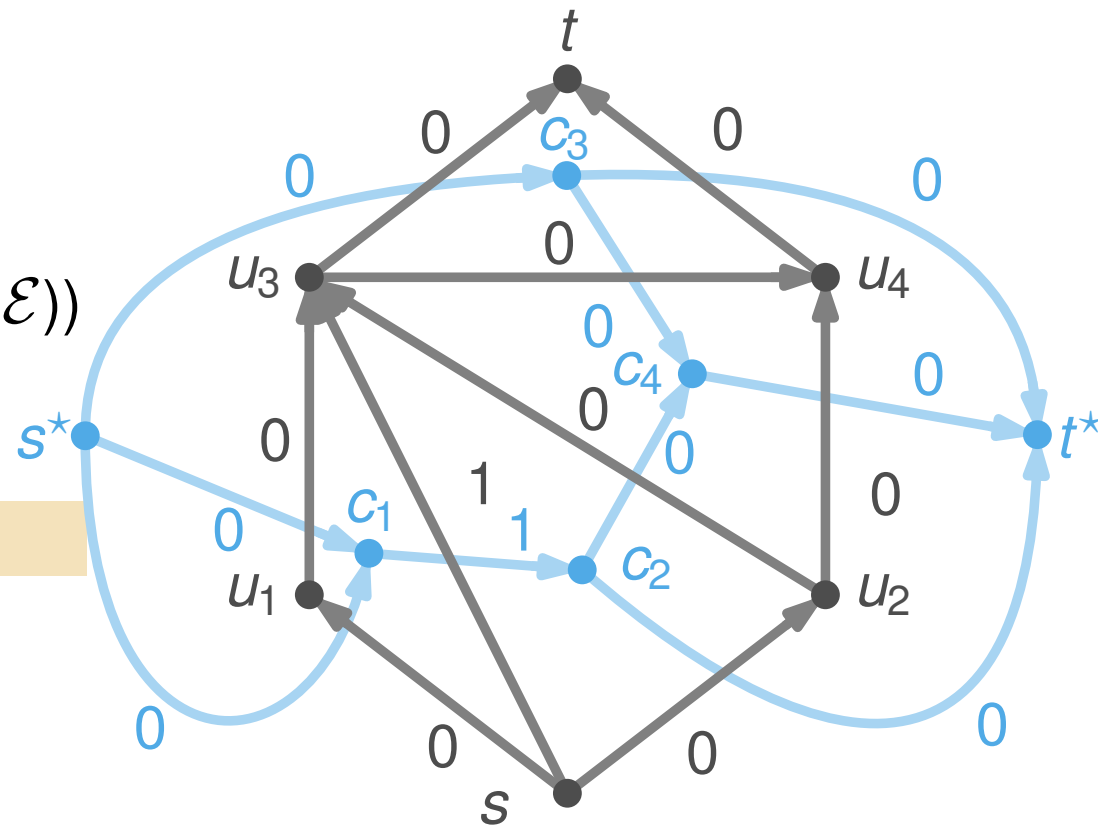
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$\mu_{\text{dual}} : E(G) \rightarrow E(G^*)$



▷ Bijective function

# Algorithmic Sketch

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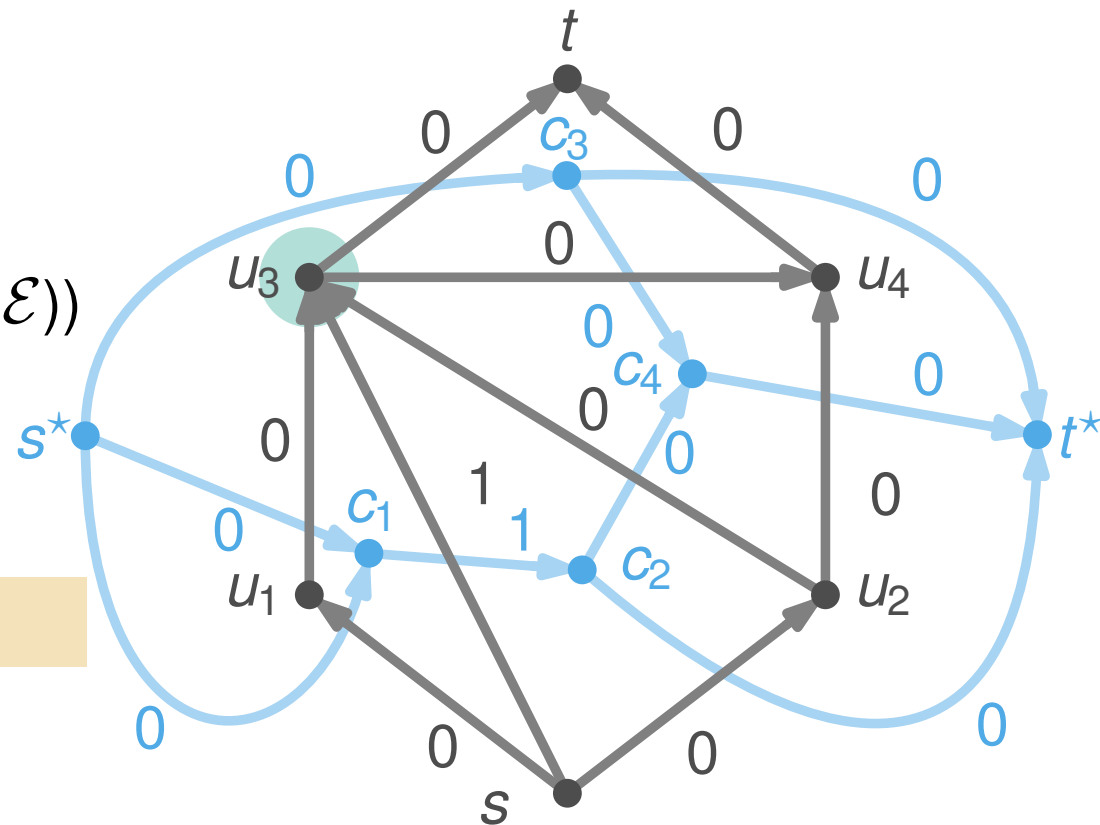
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$\mu_{\text{dual}} : E(G) \rightarrow E(G^*)$

$X = \bigcup_{u \in V(G) : f_{\text{net}}(u) \neq 0} \{u\}$



▷ Check KCL property in graph  $G$

# Algorithmic Sketch

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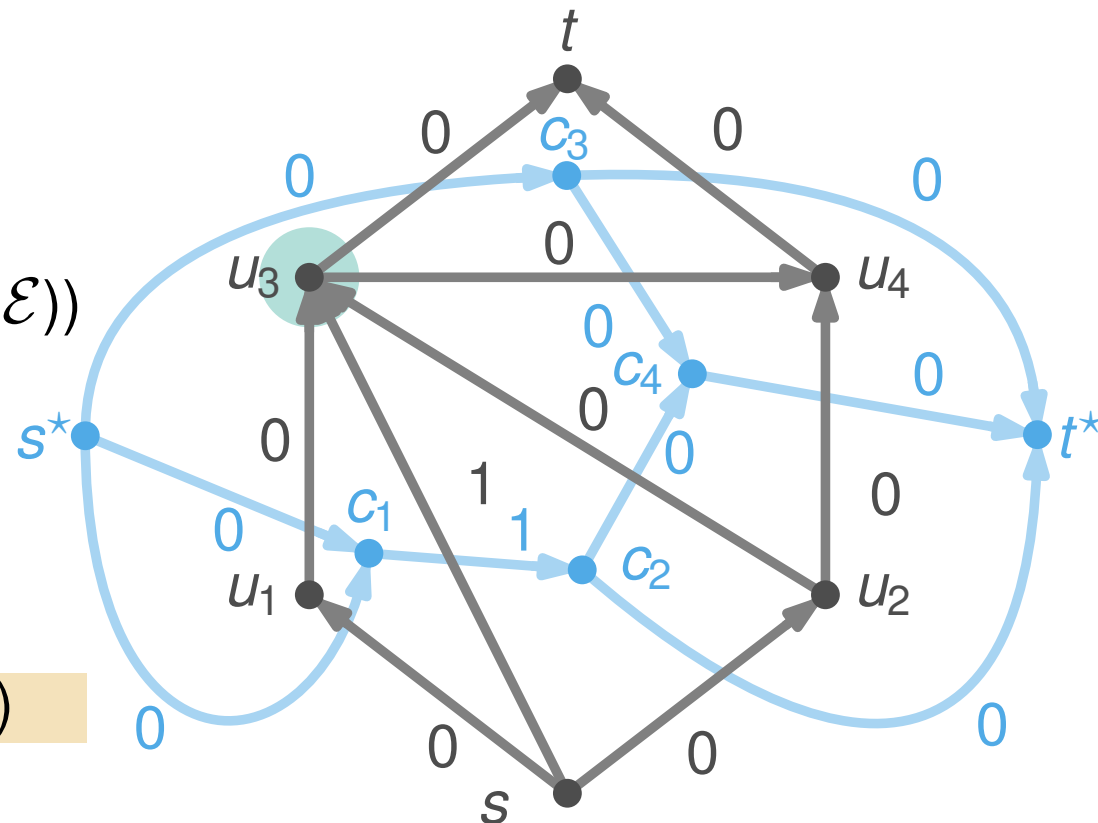
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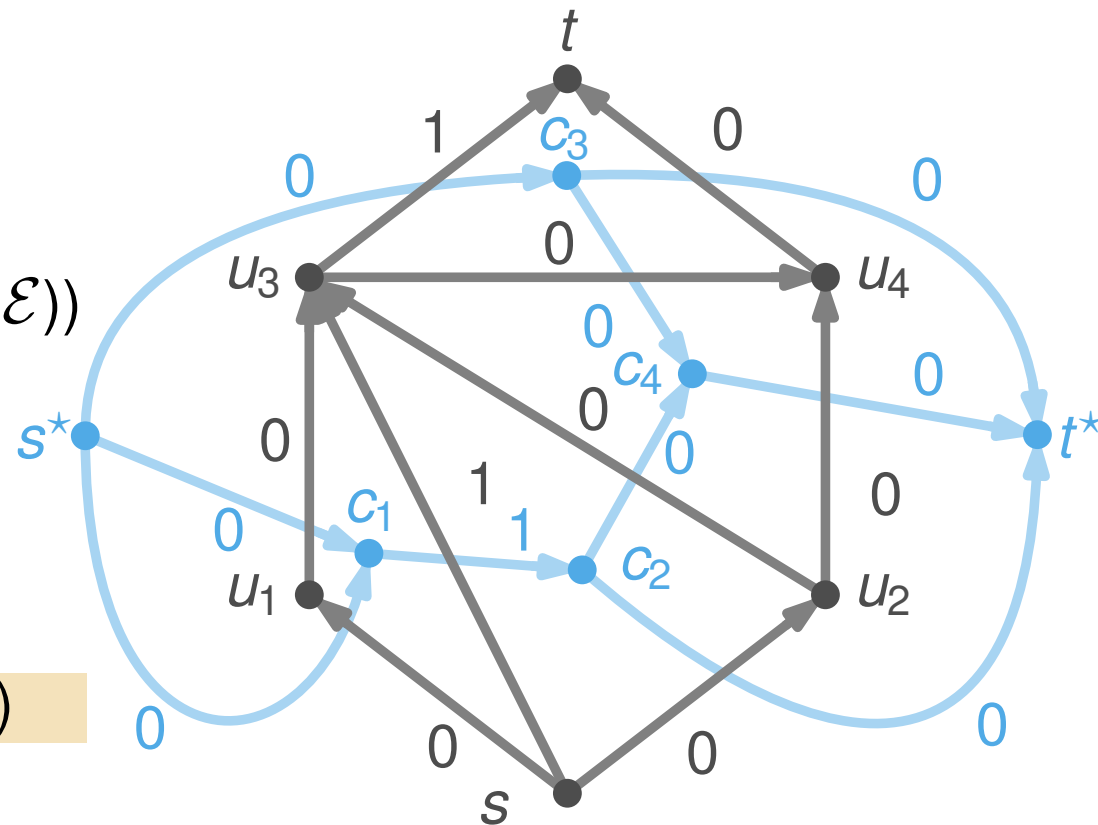
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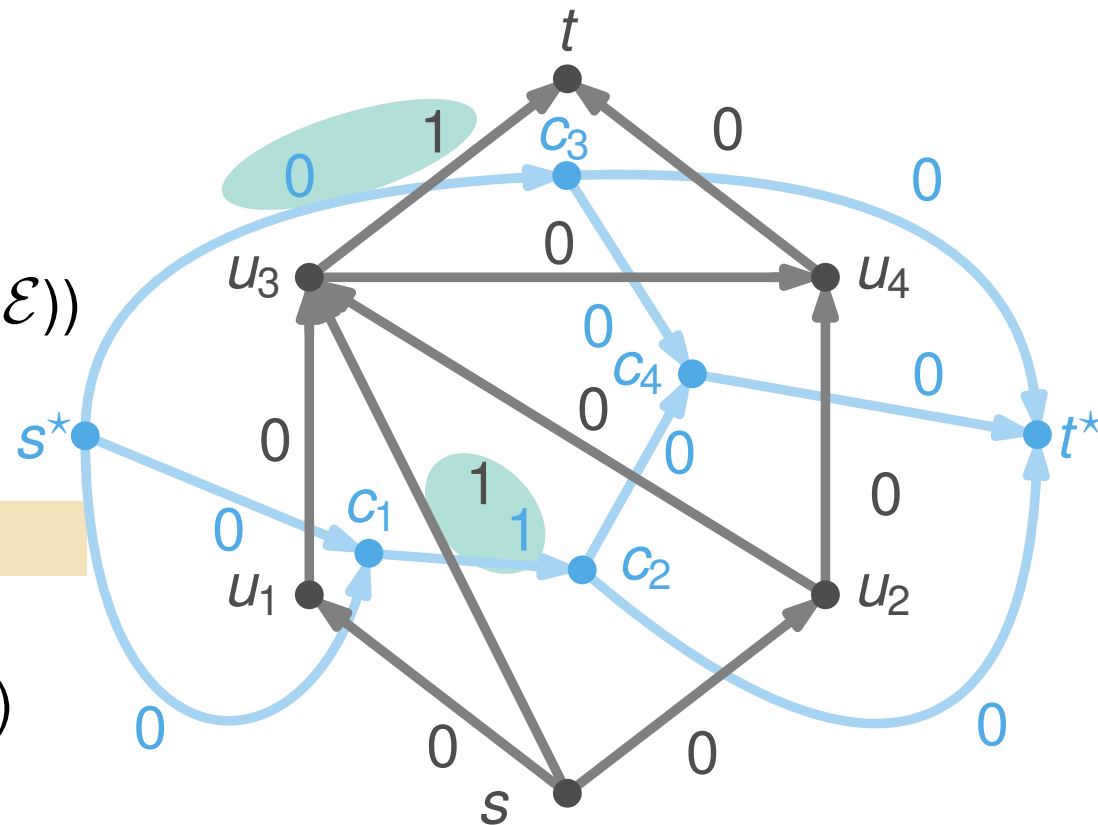
$f \equiv 0$

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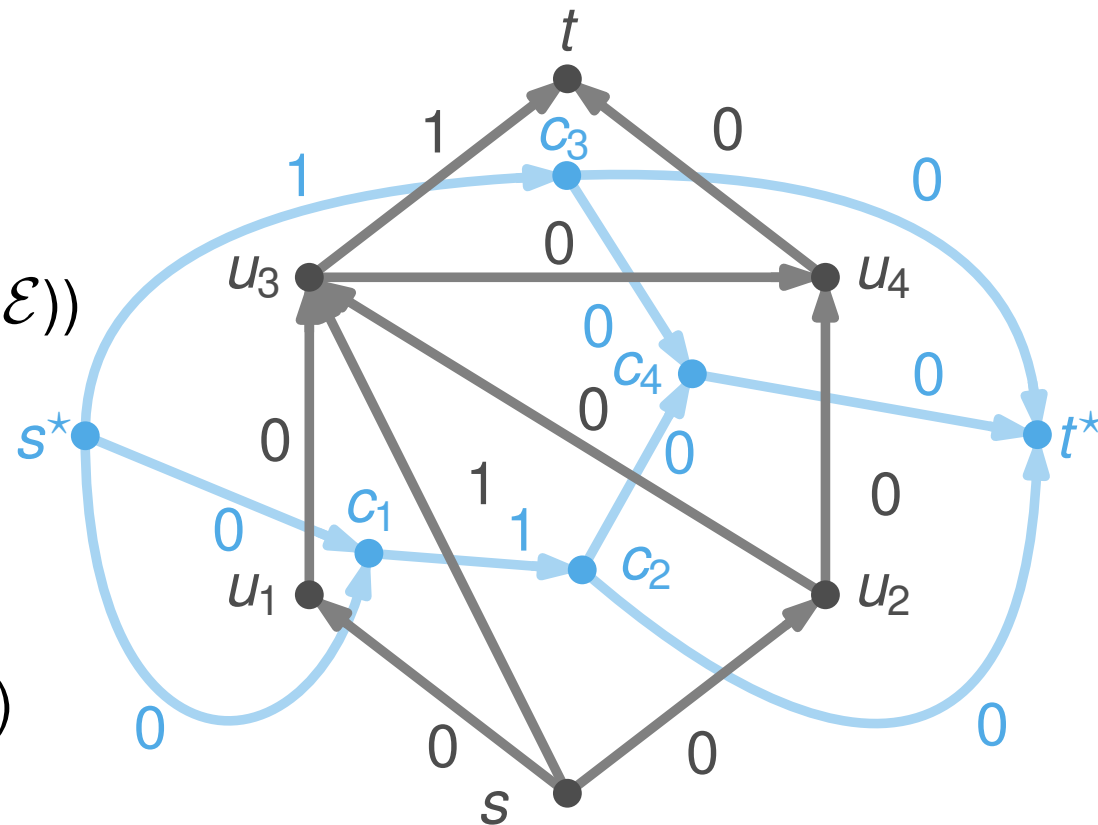
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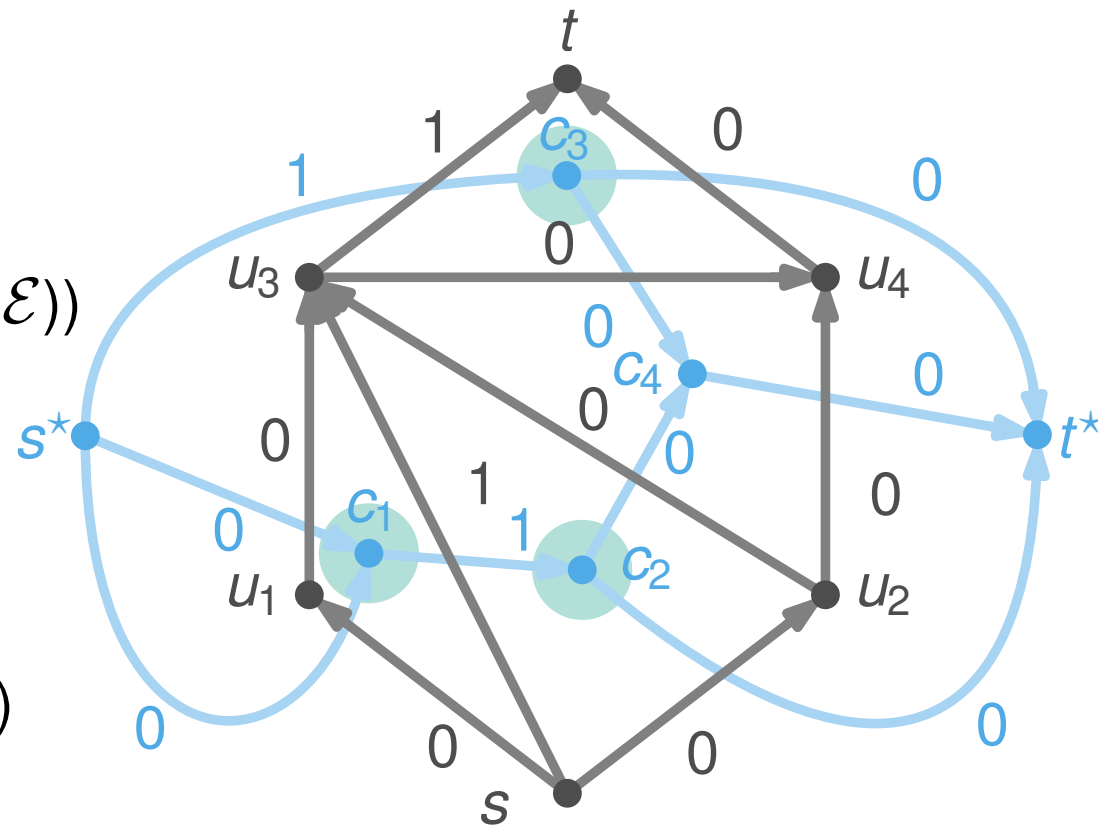
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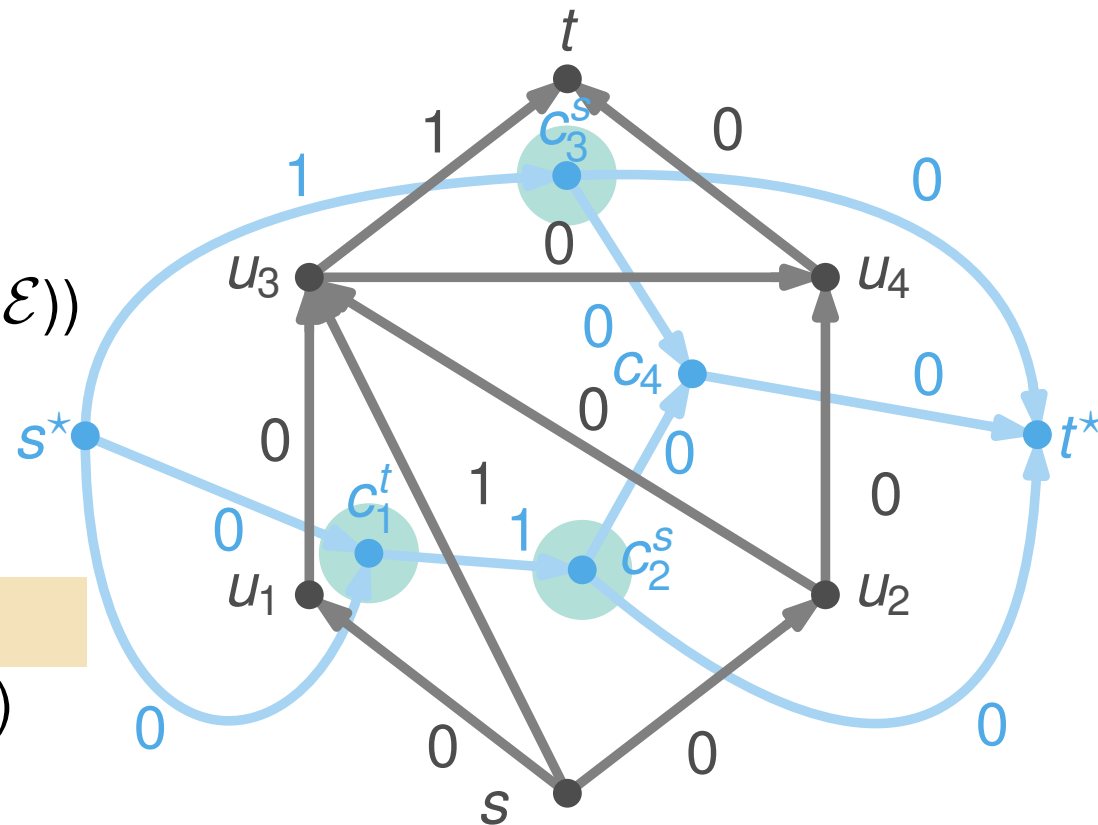
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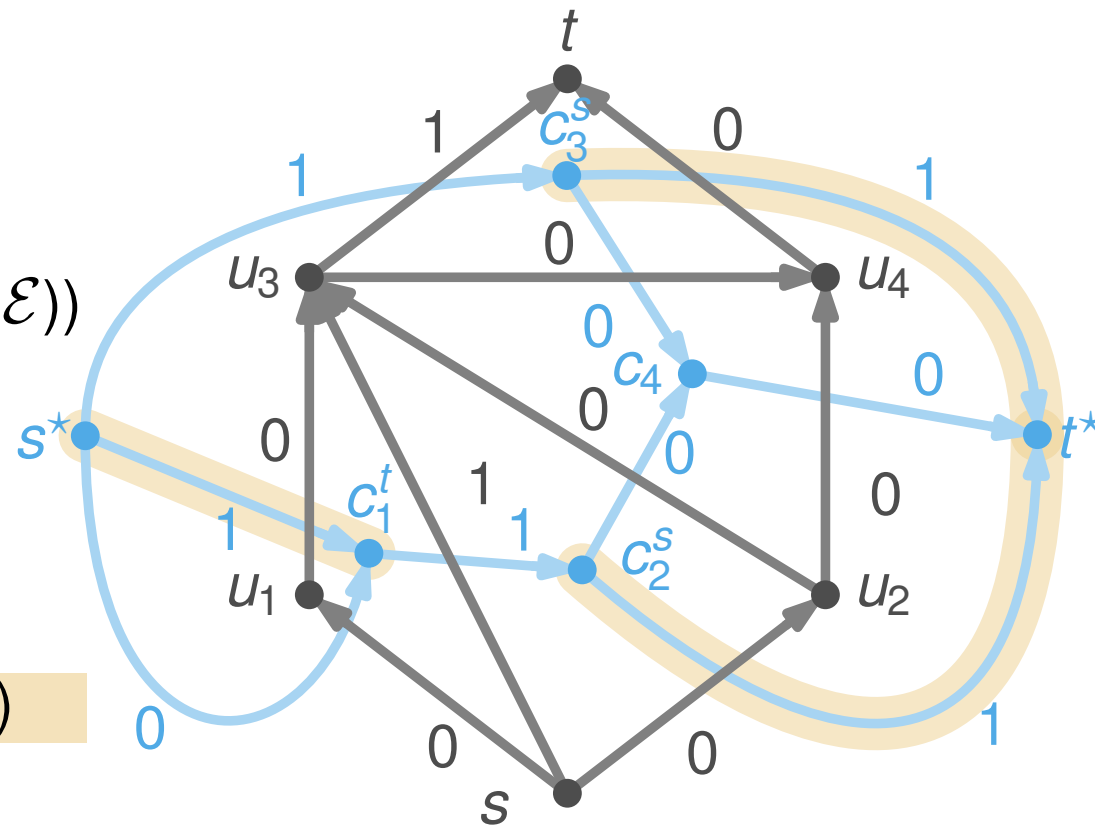
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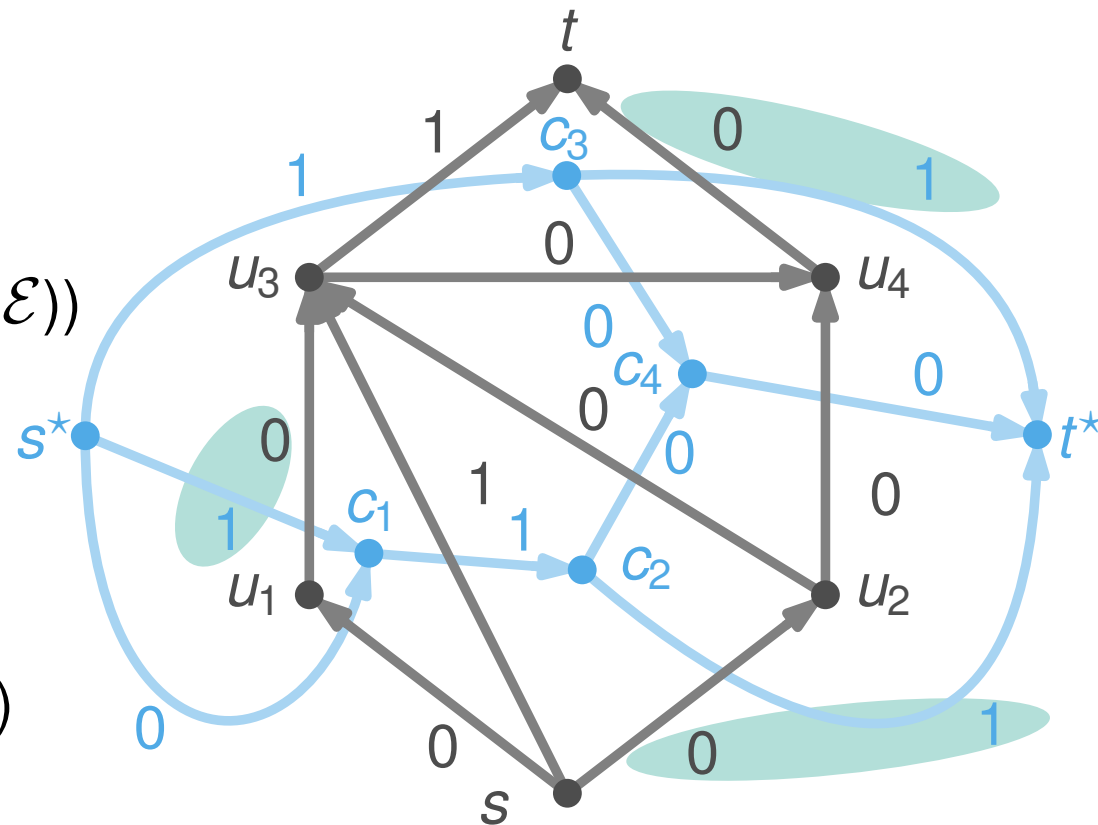
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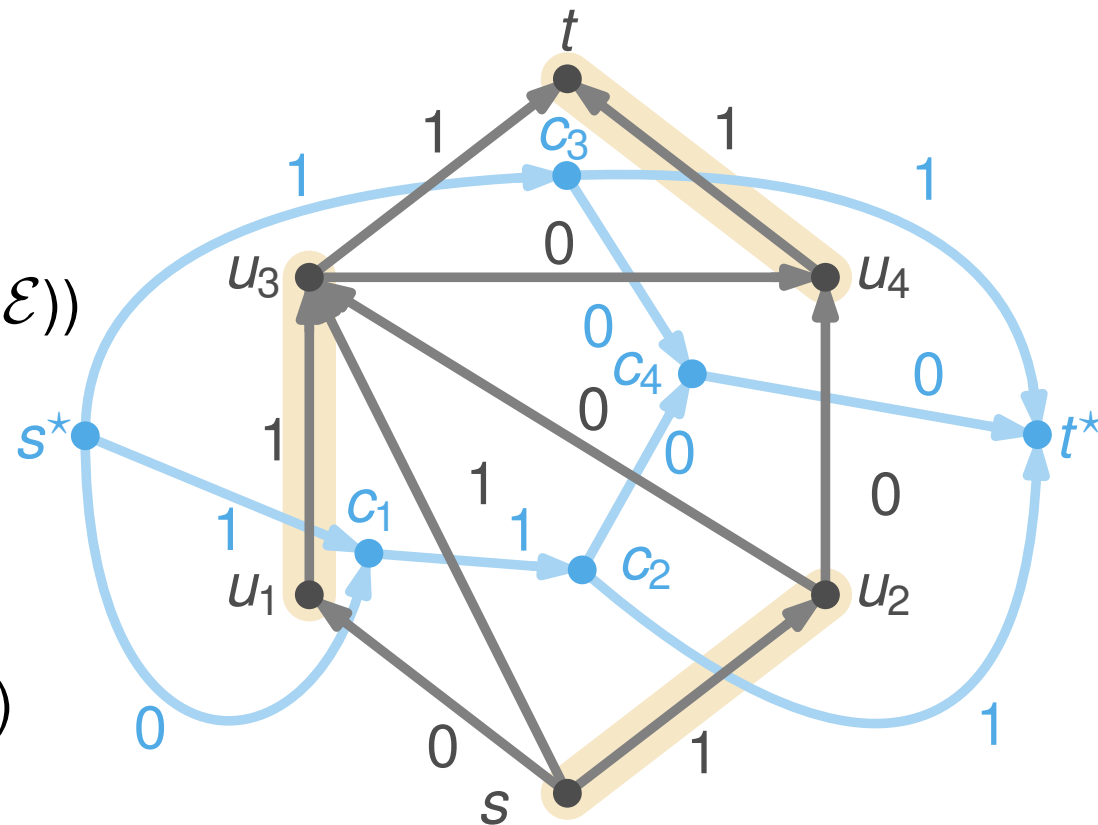
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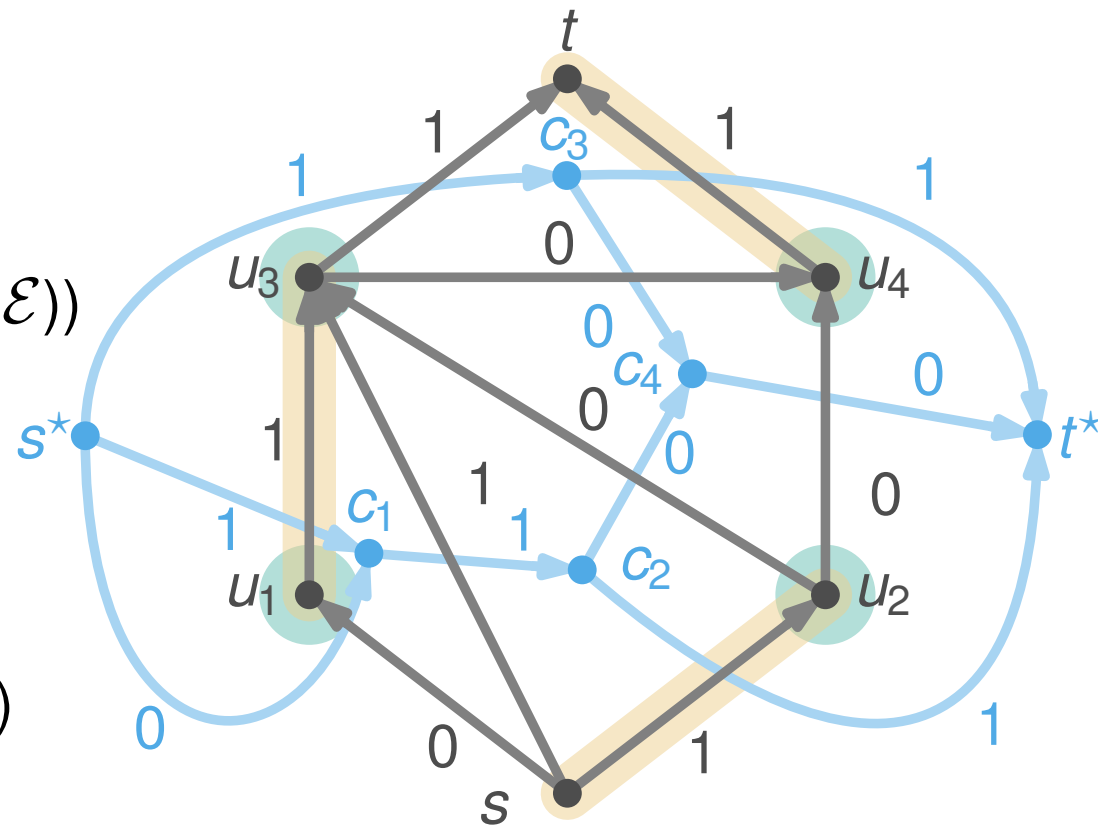
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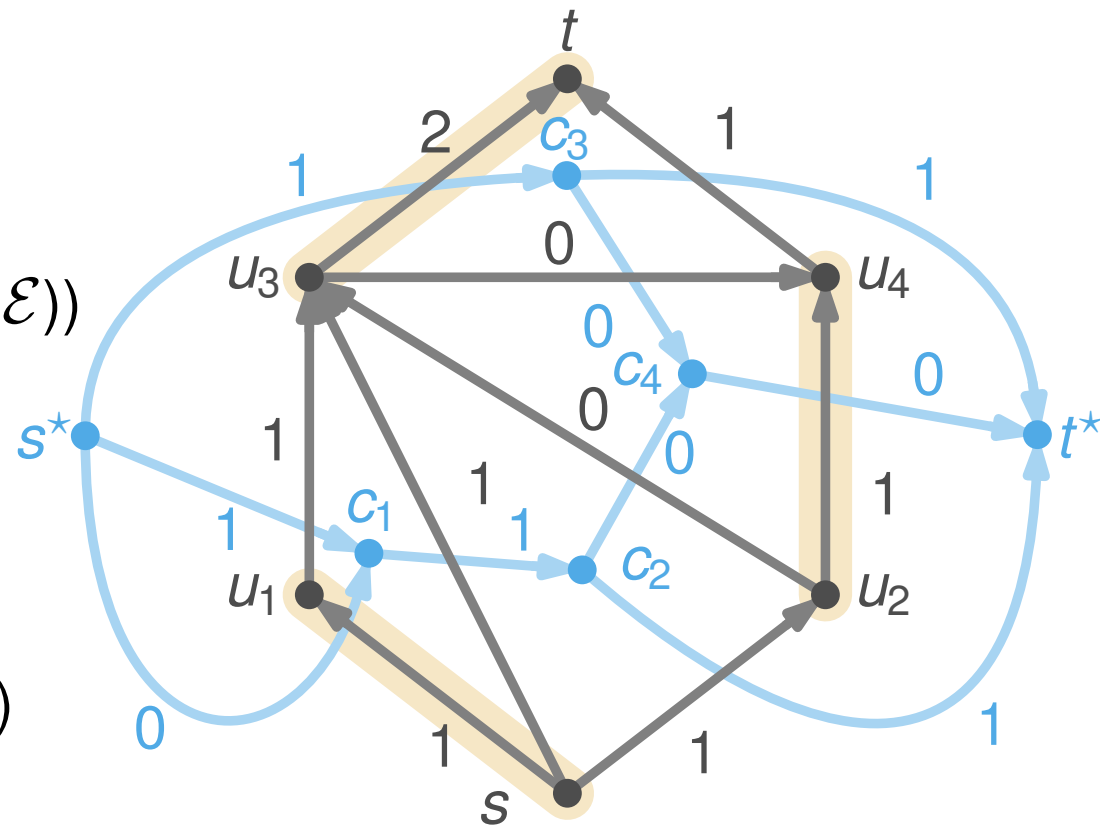
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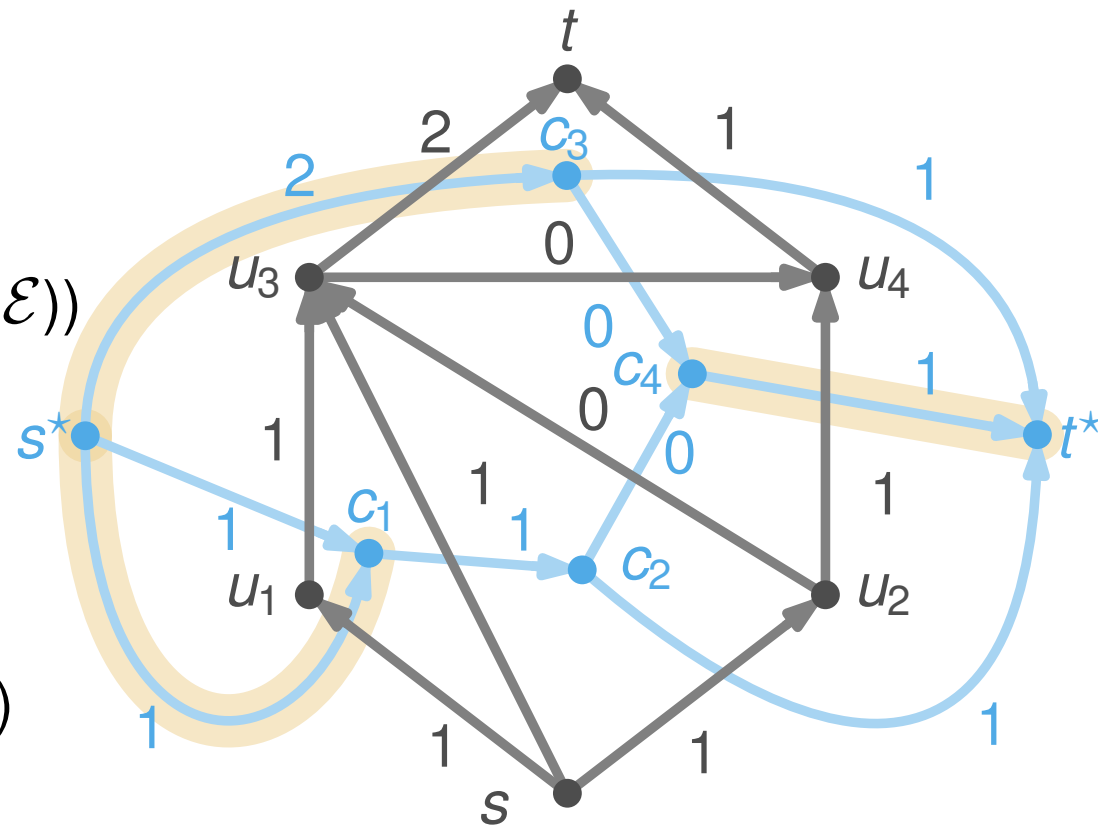
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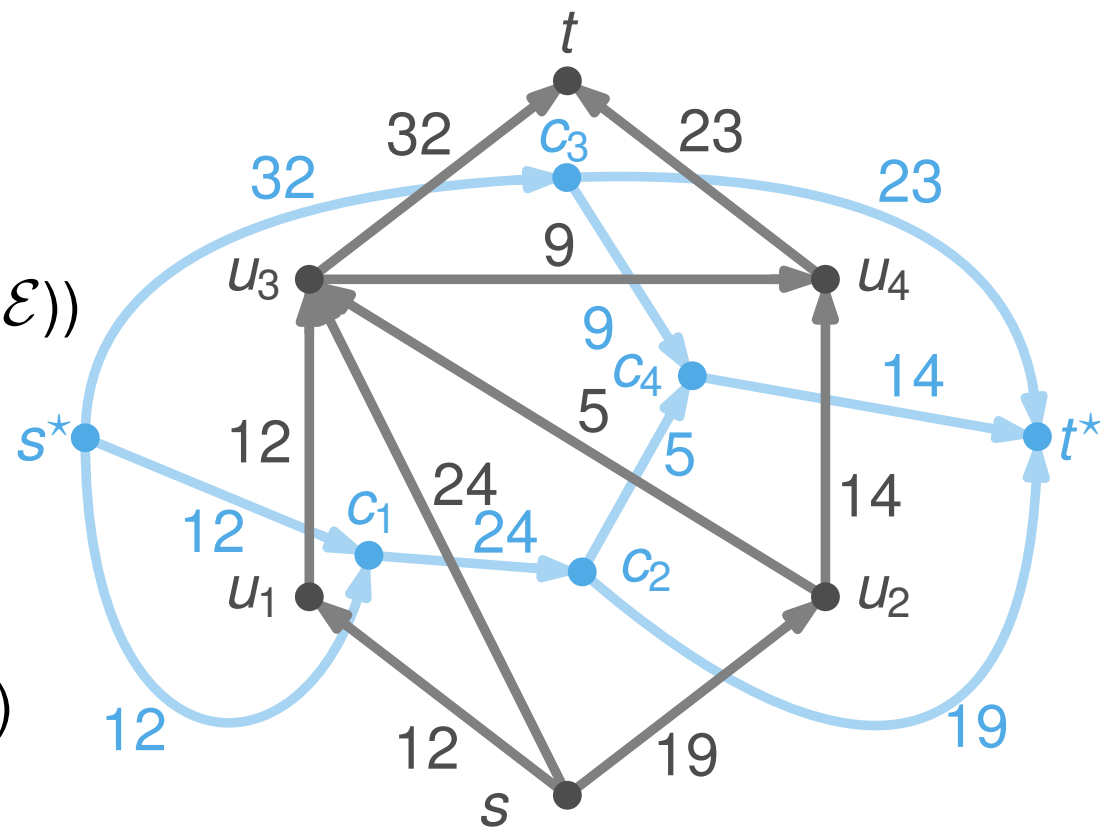
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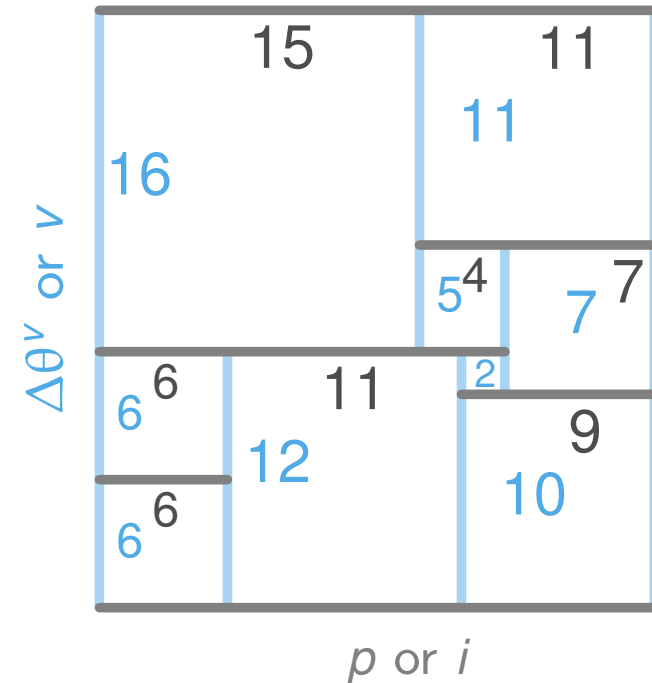
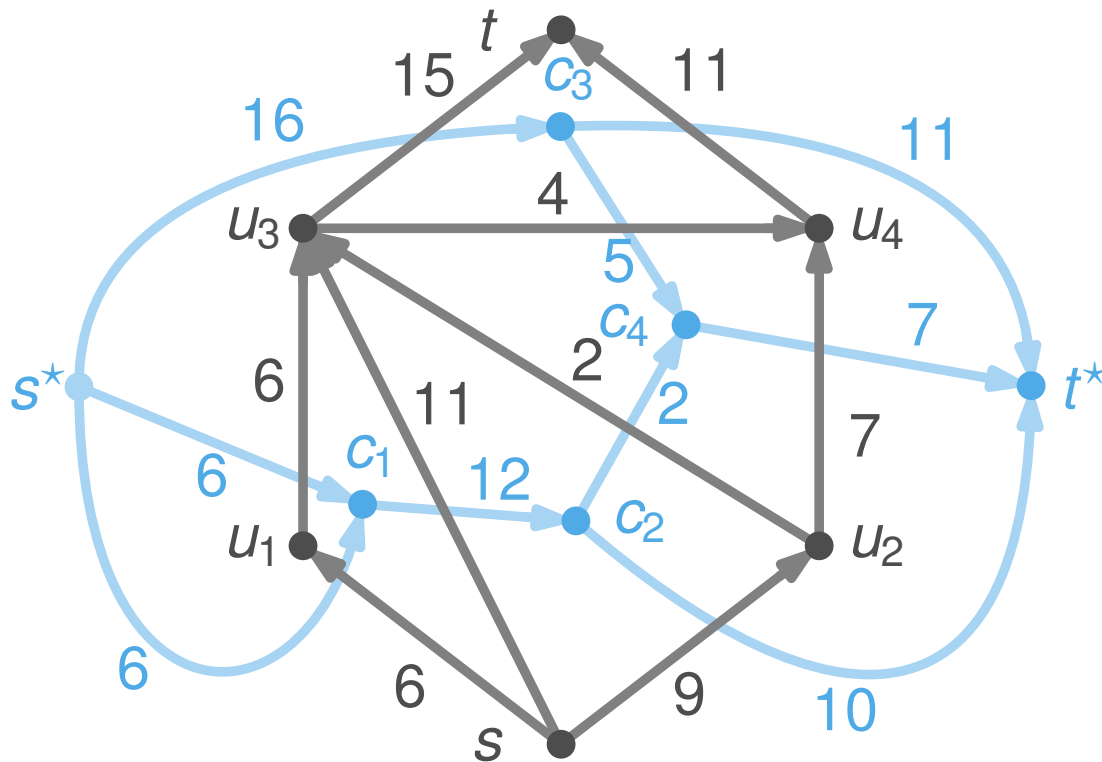
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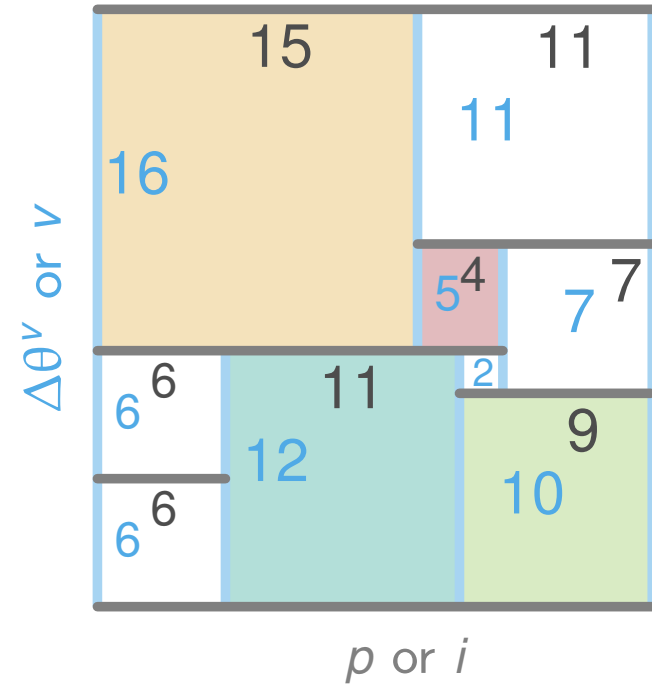
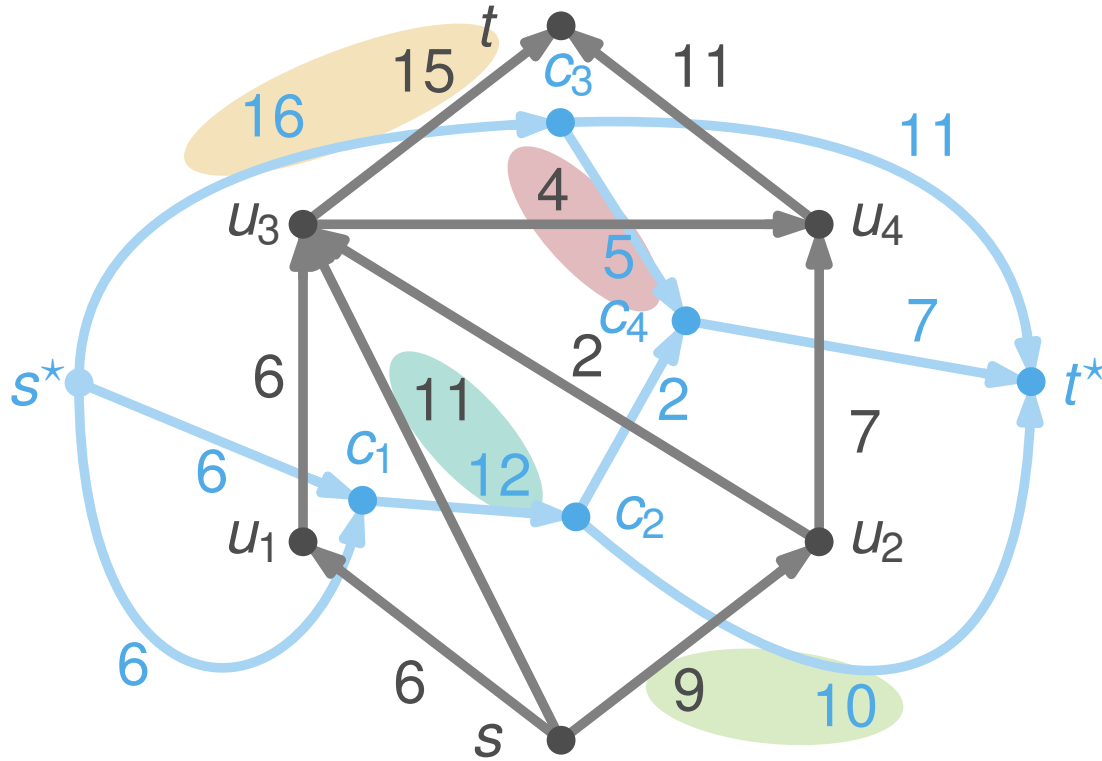
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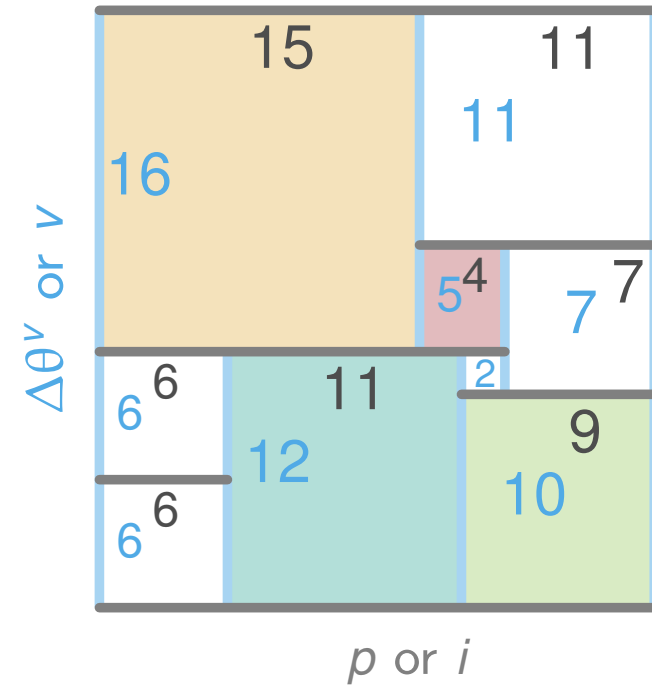
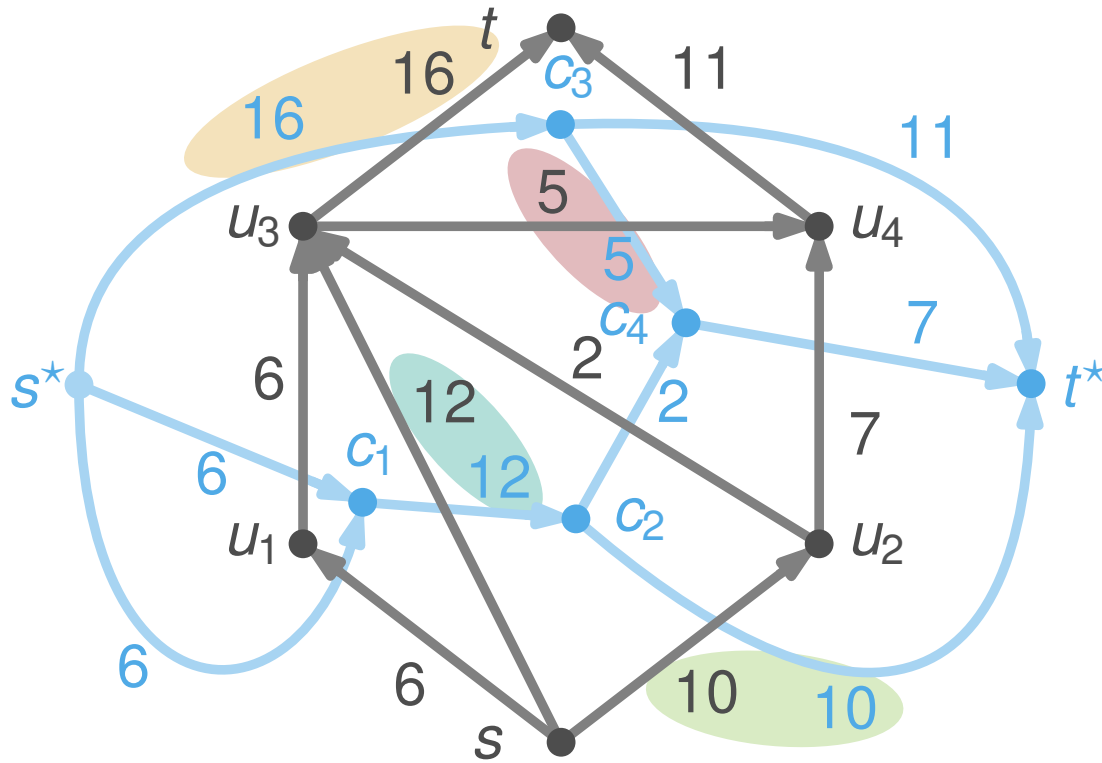
# Geometric Interpretation of a KCL Conflict



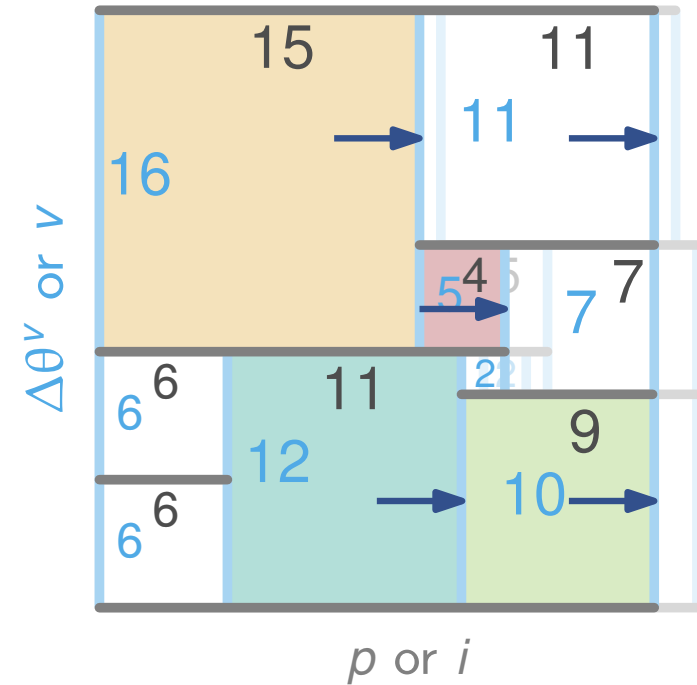
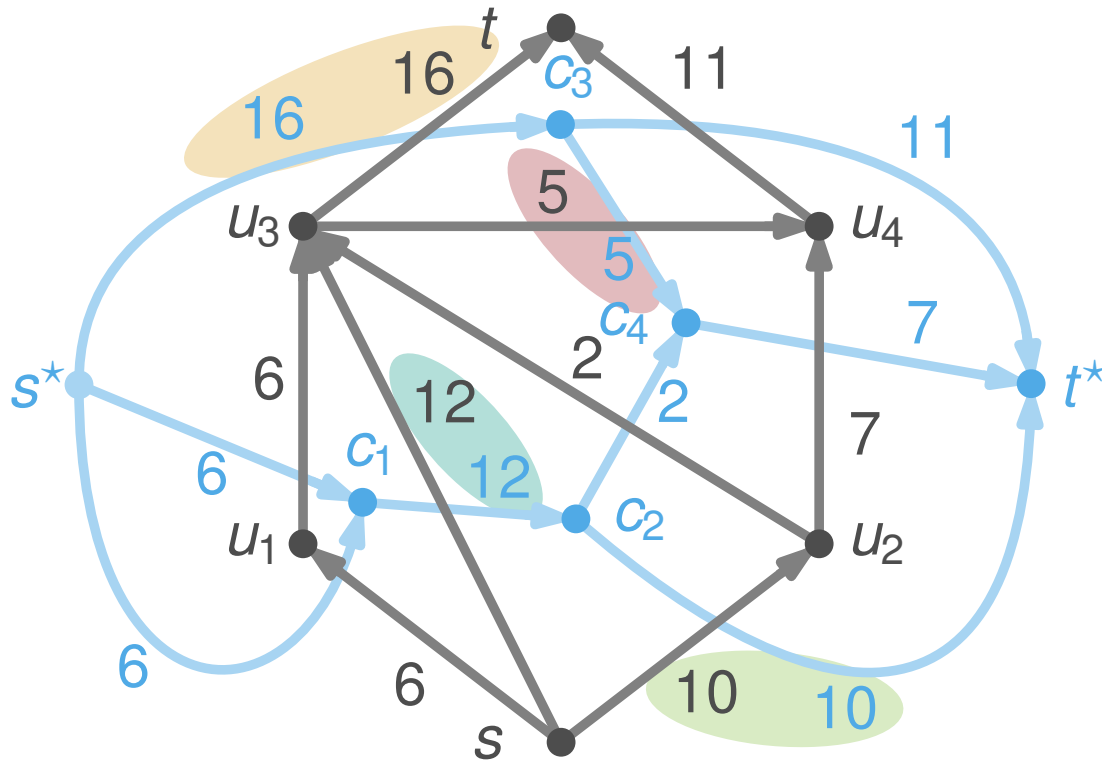
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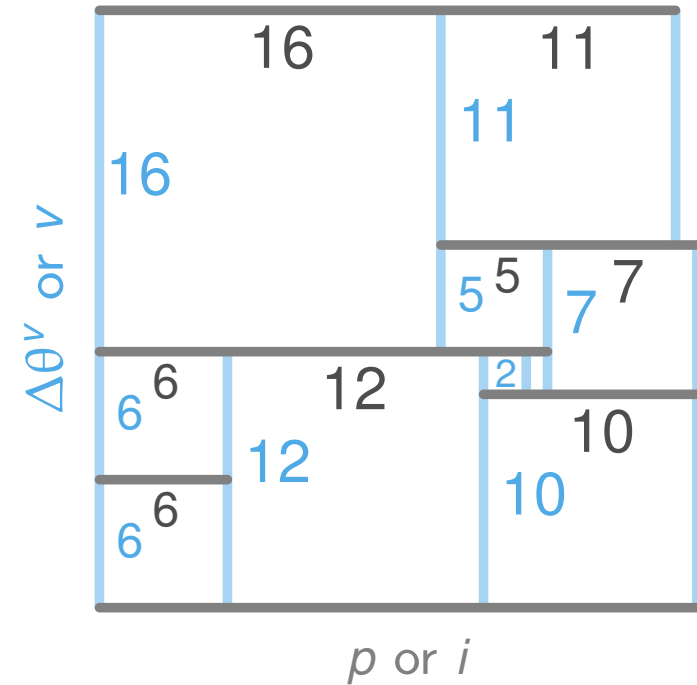
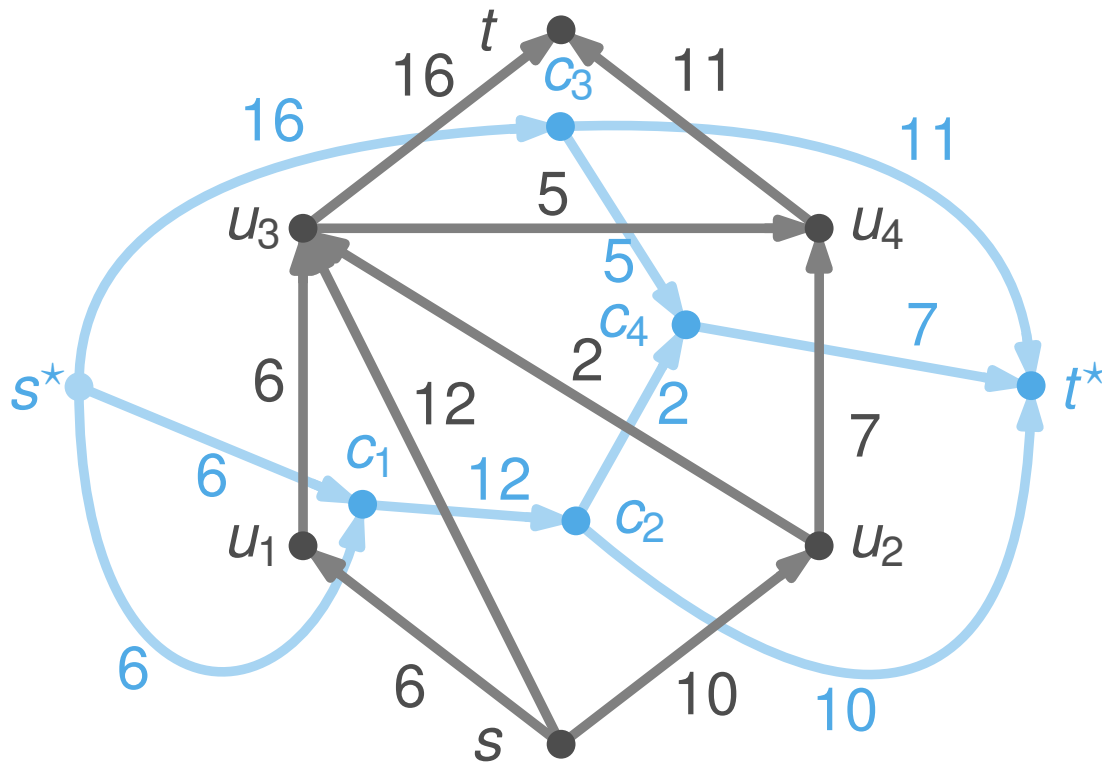
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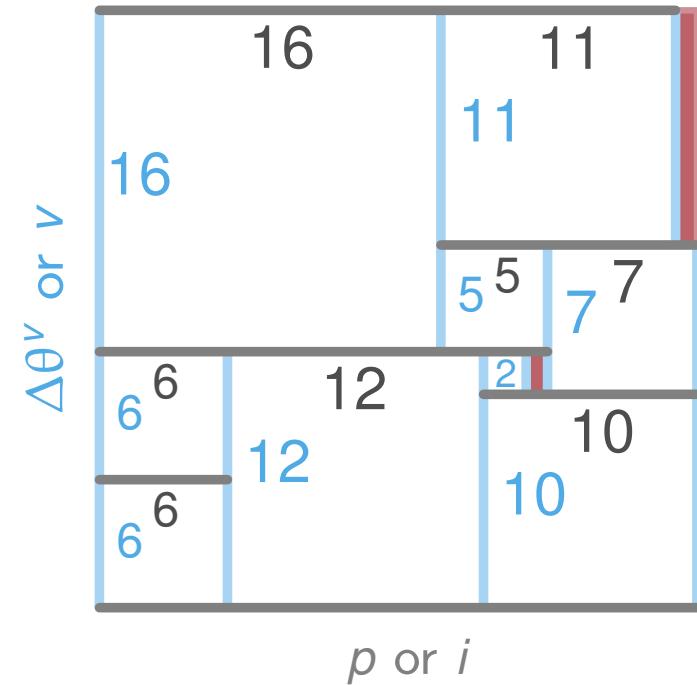
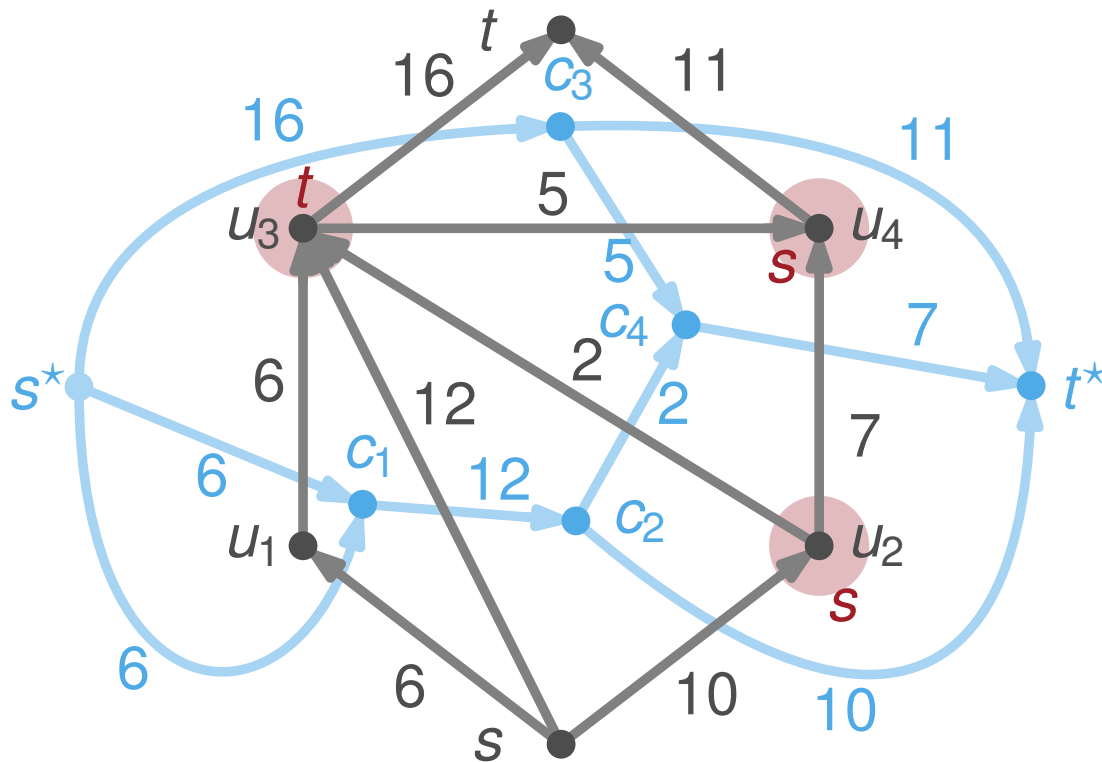
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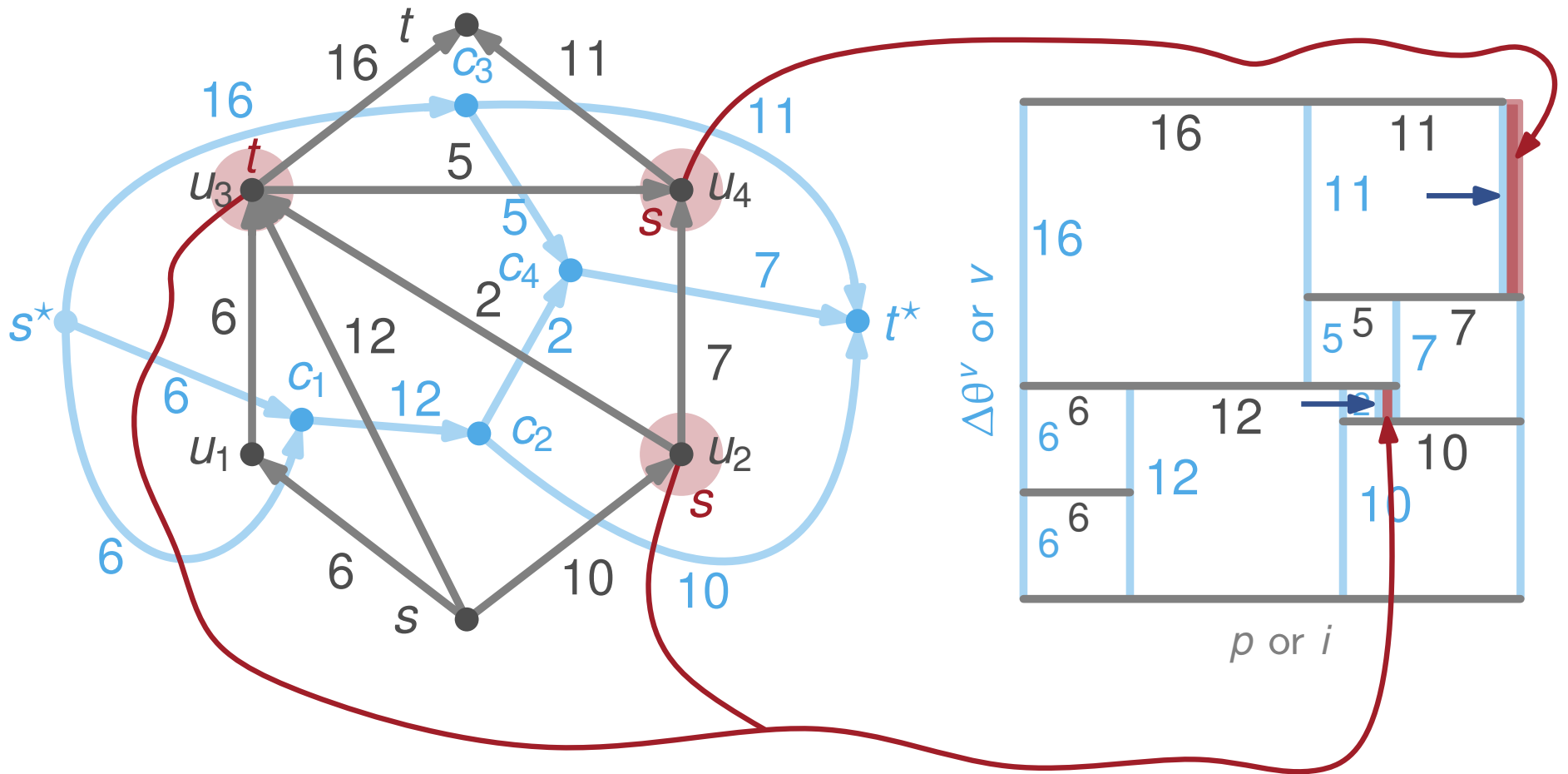
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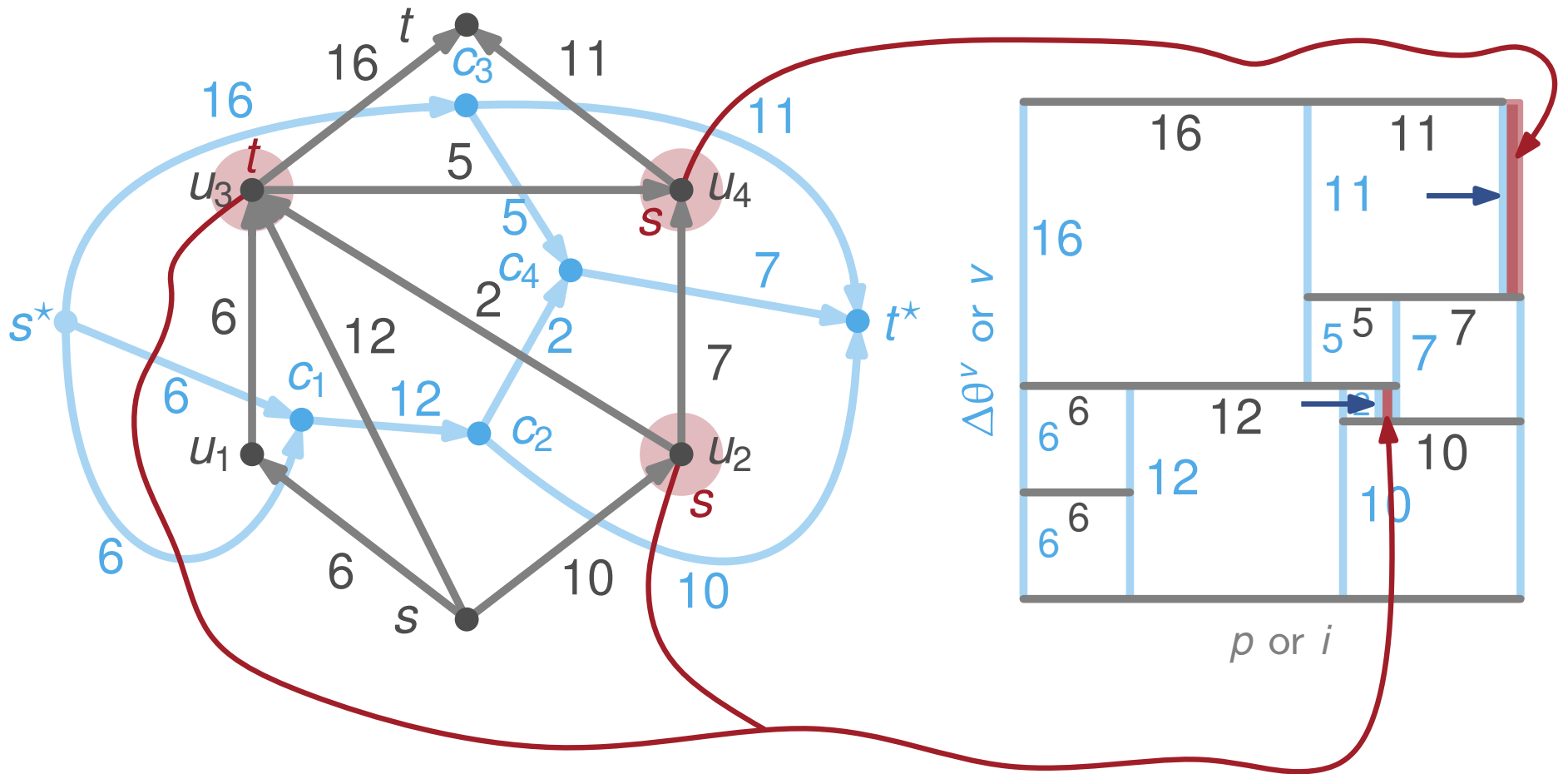


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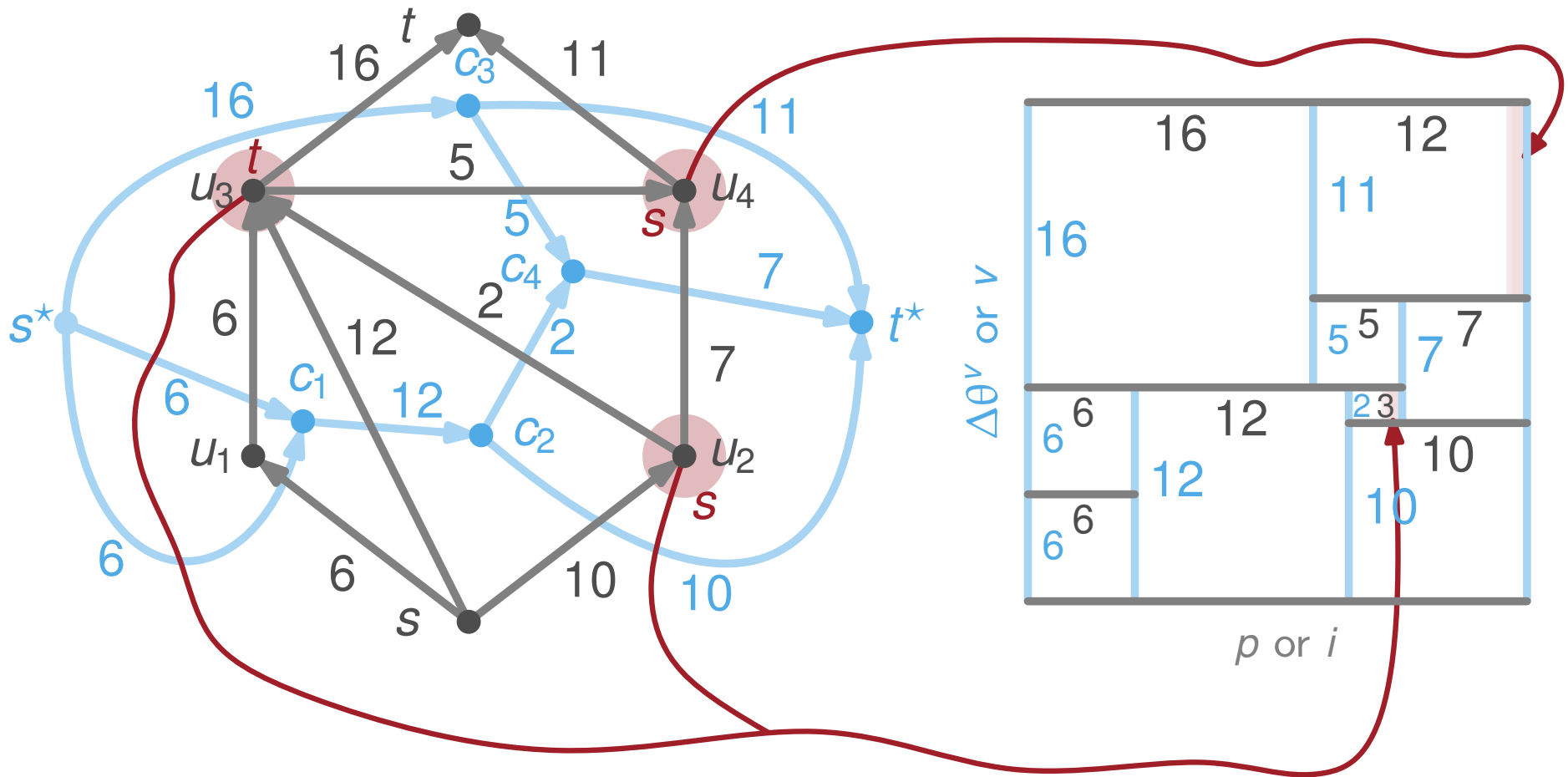




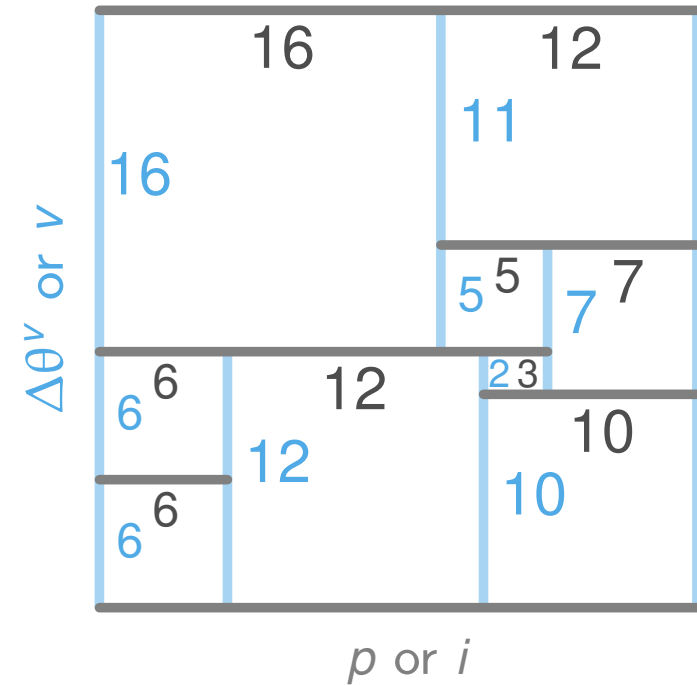
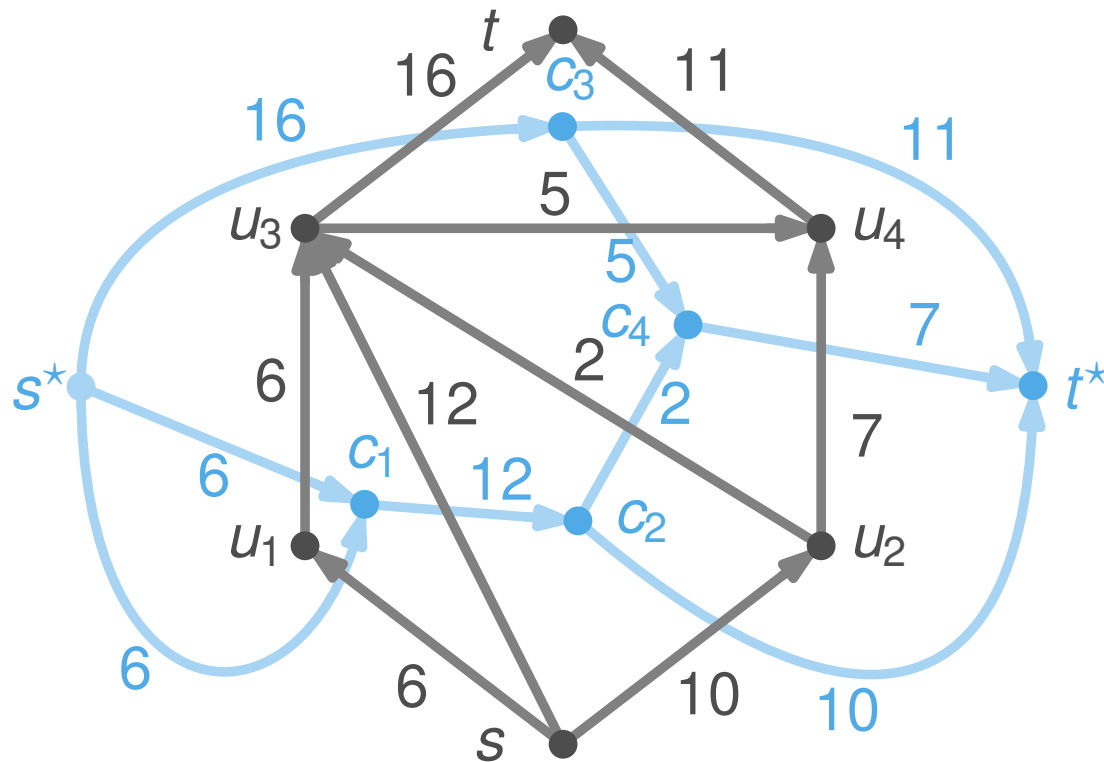
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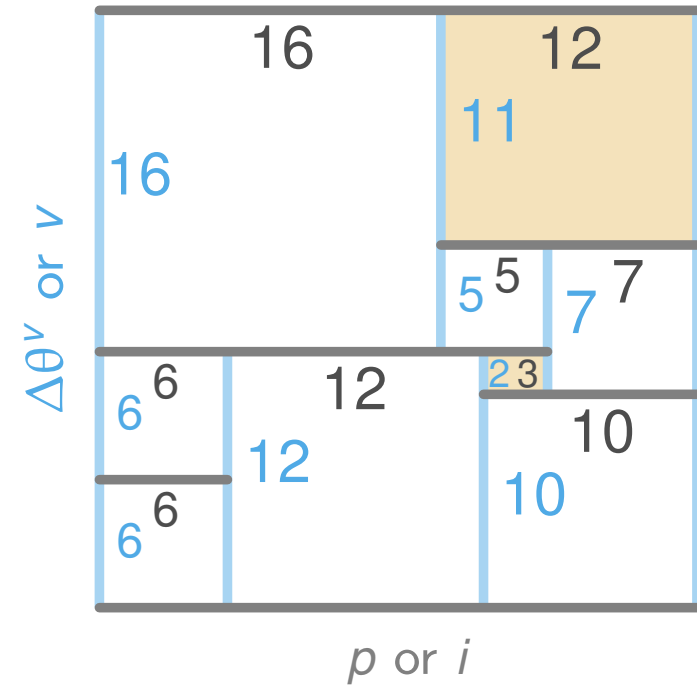
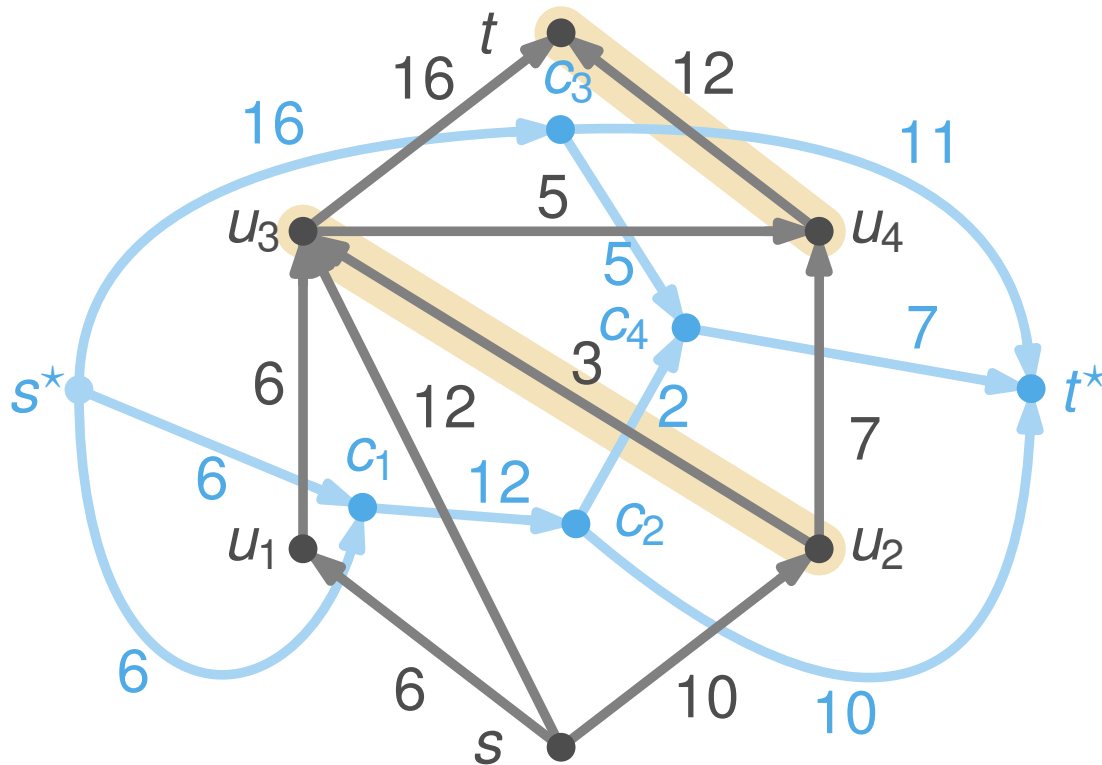
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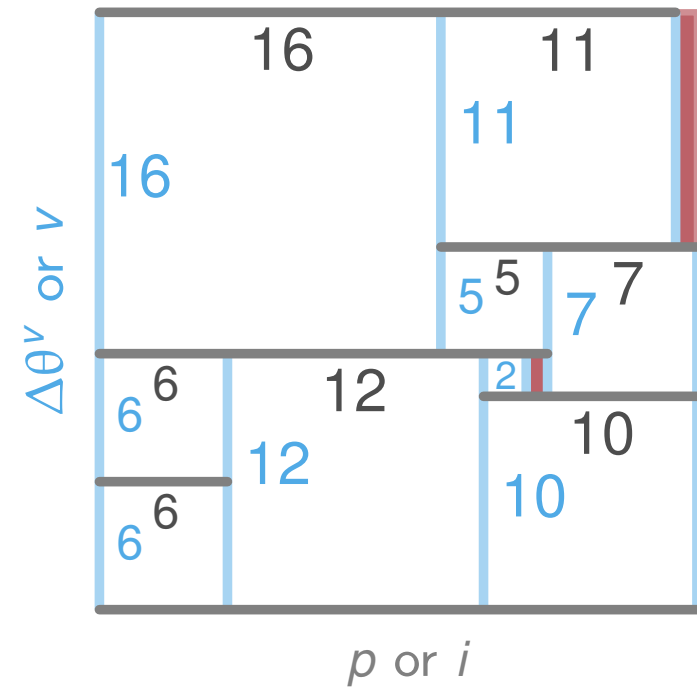
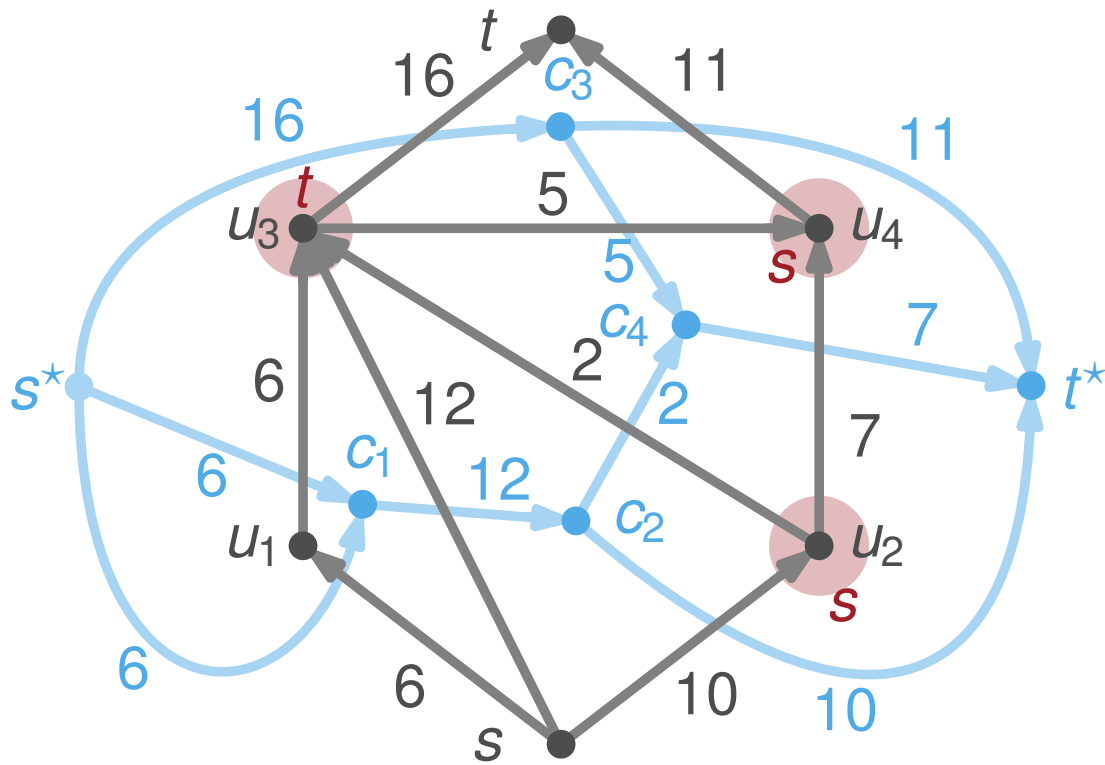
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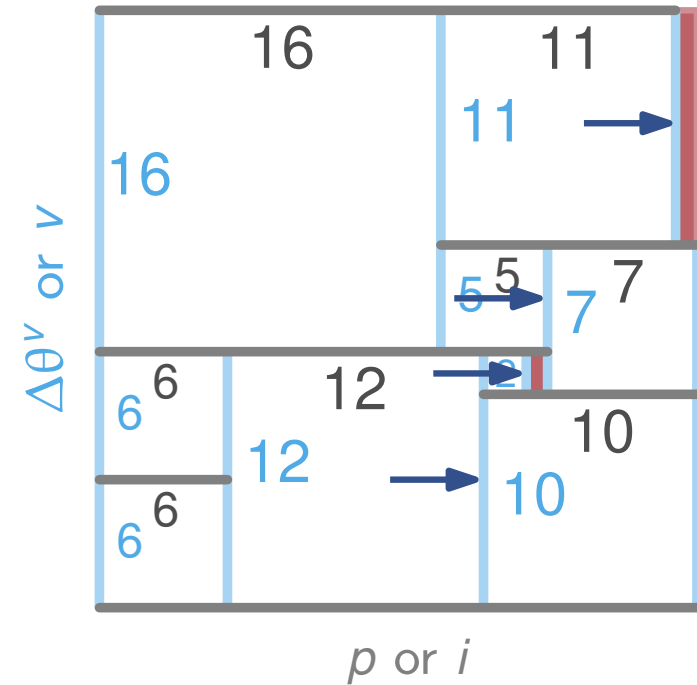
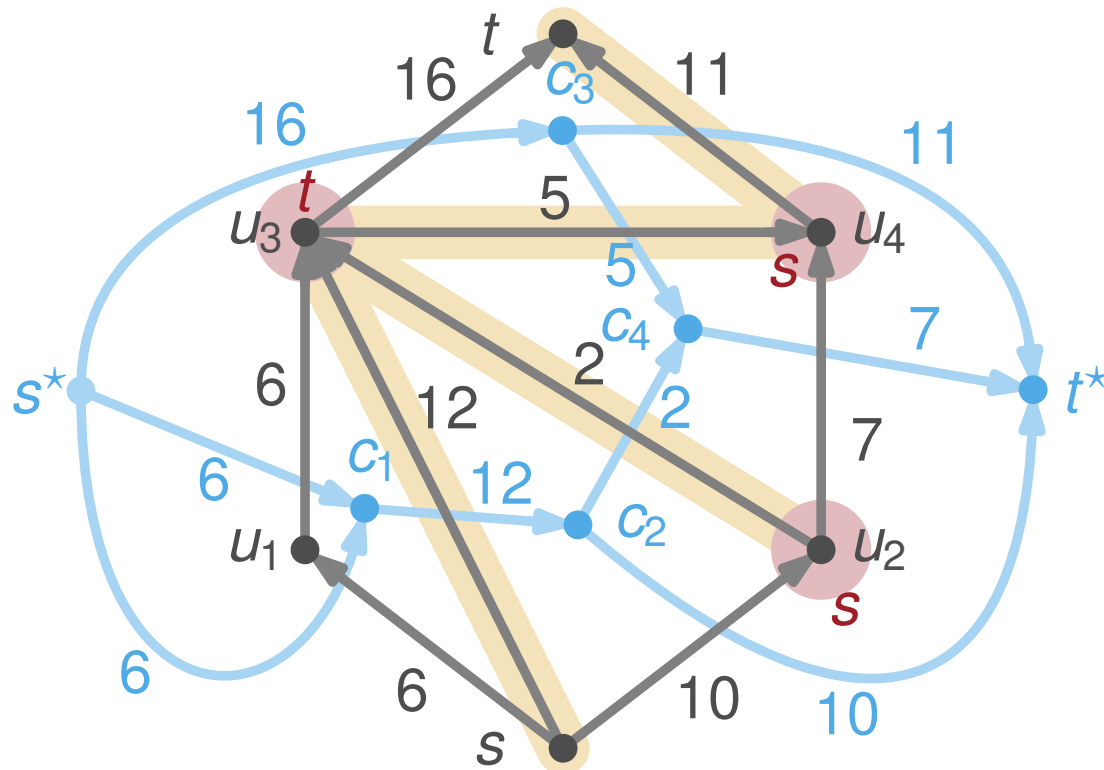
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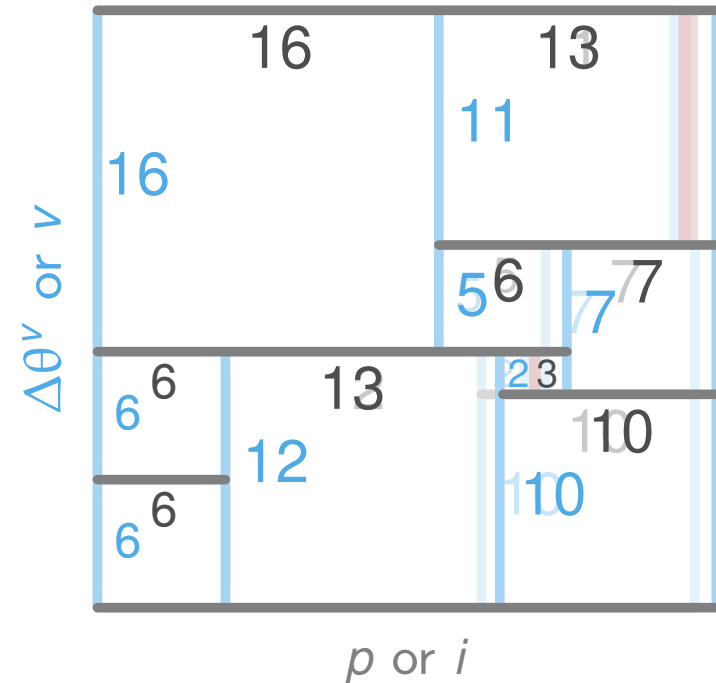
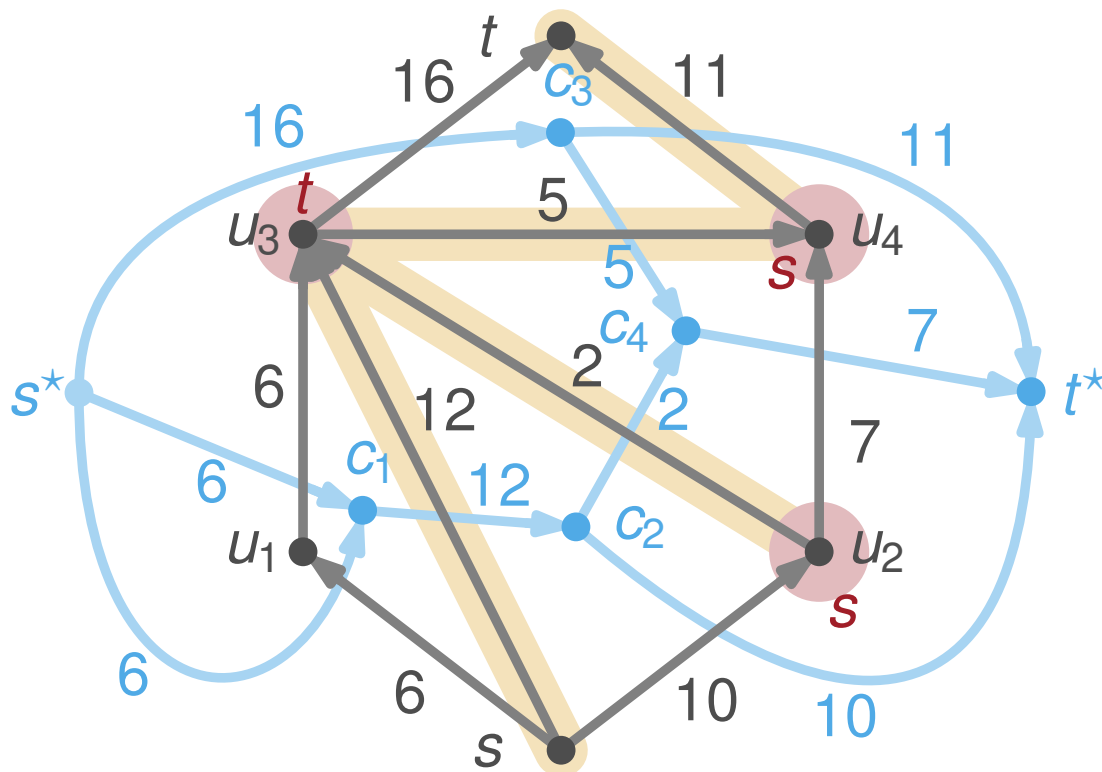
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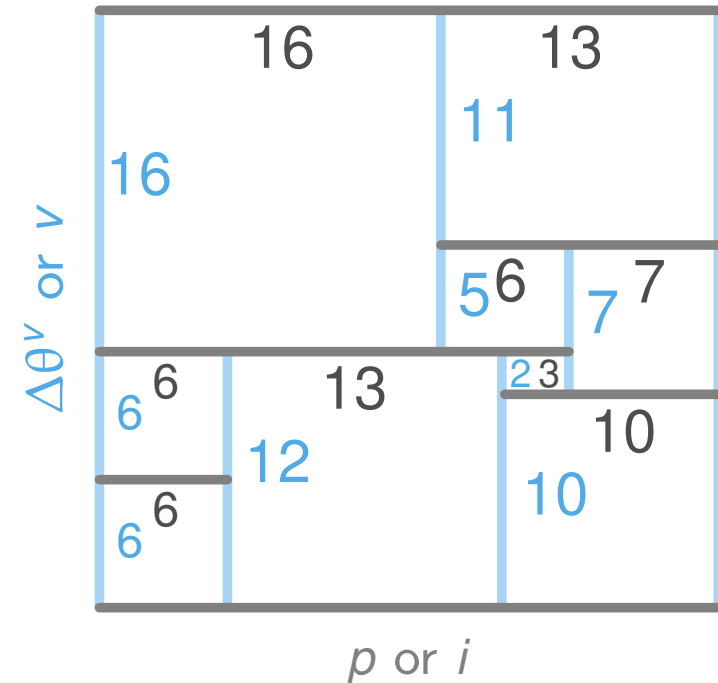
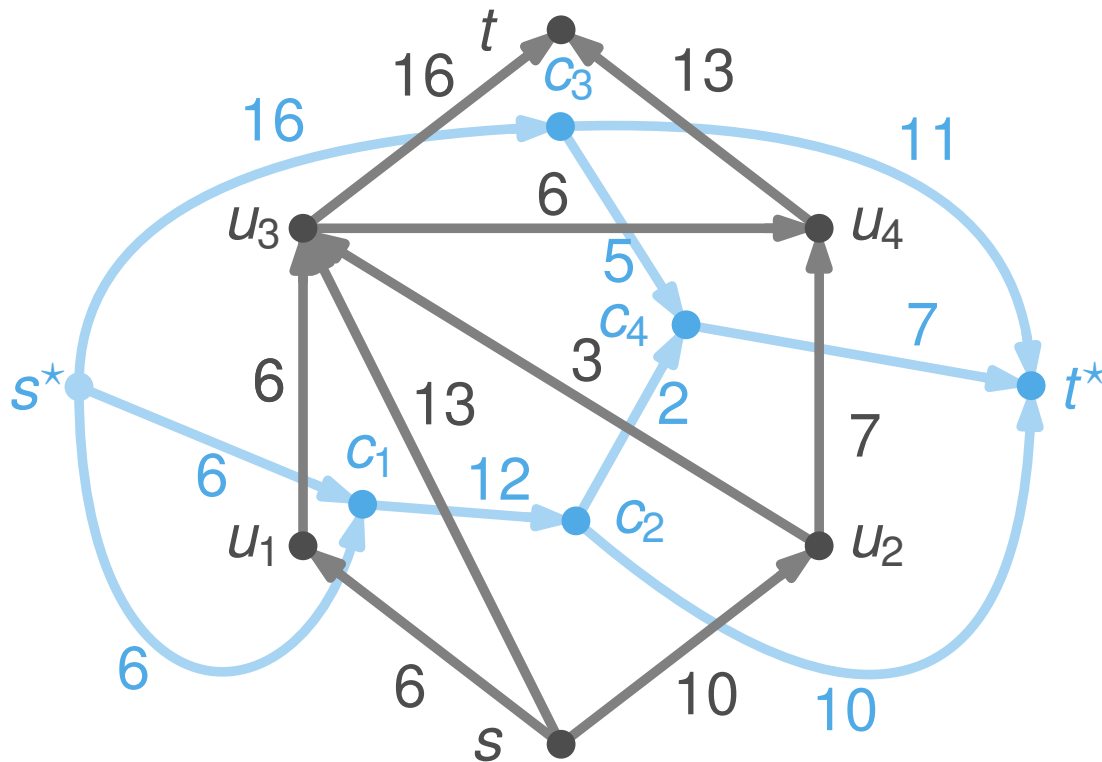
# Geometric Interpretation of a KCL Conflict



## Observation 5 [Resolve KCL Conflicts]

Minimize in each `resolveConflict` step the total resizing of the outer rectangle, since a too large increase might skip a valid solution.

# Geometric Interpretation of a KCL Conflict

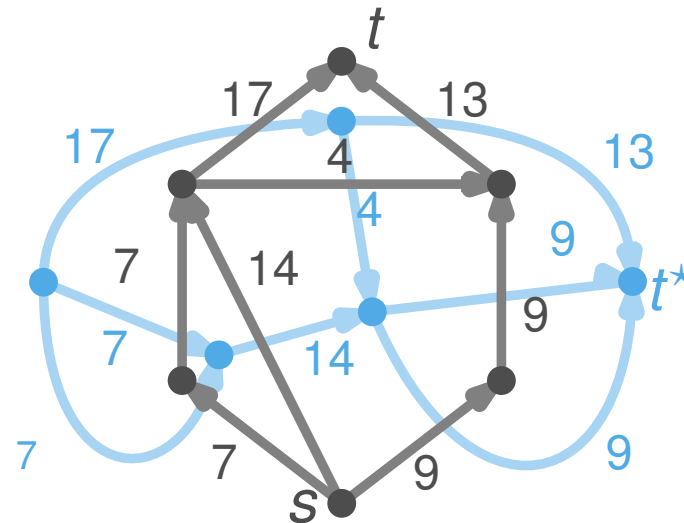
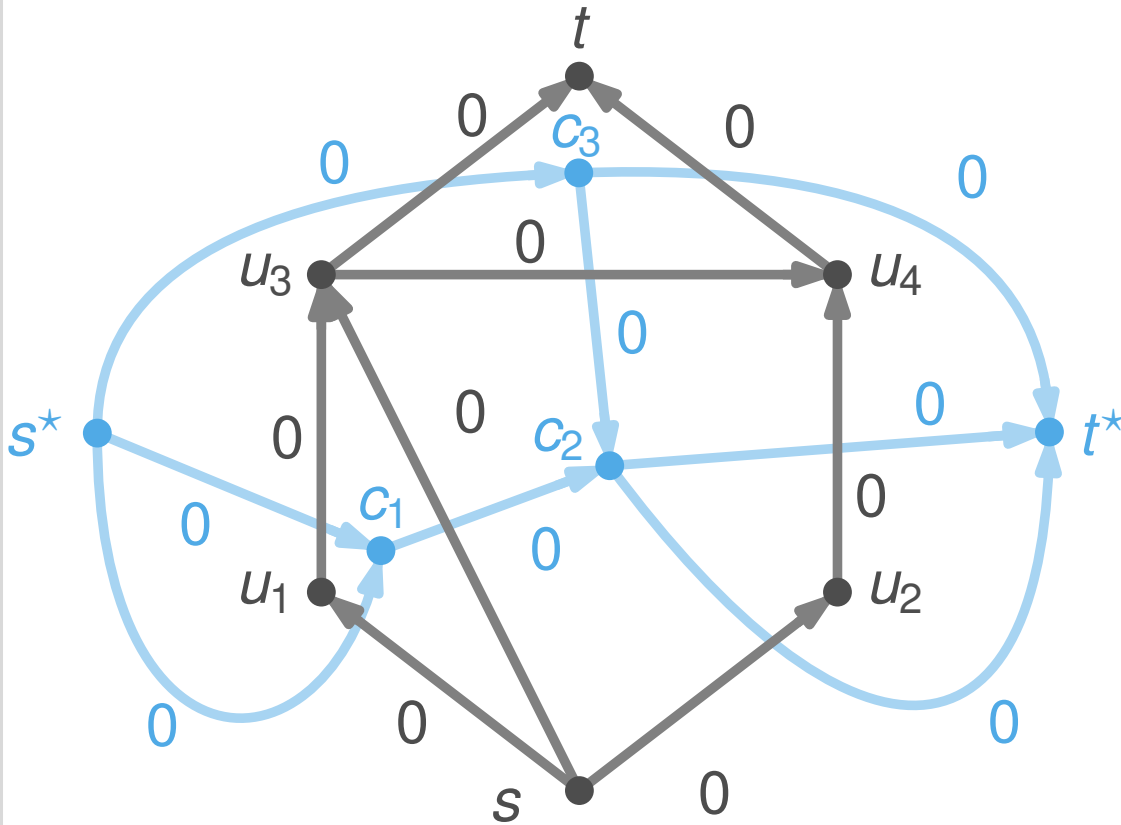


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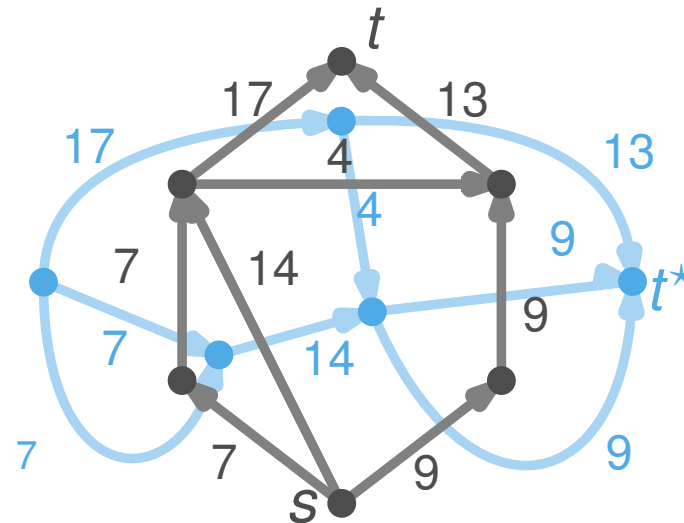
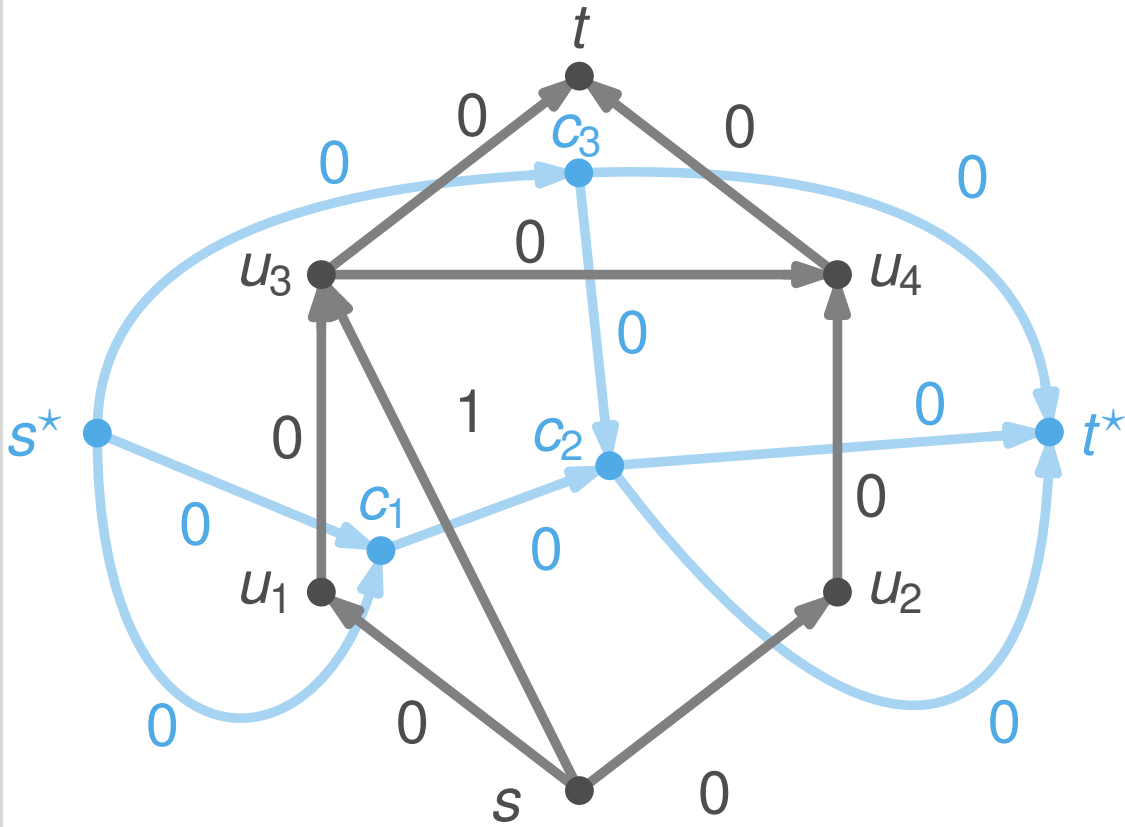


# Wrong Conflict Resolution



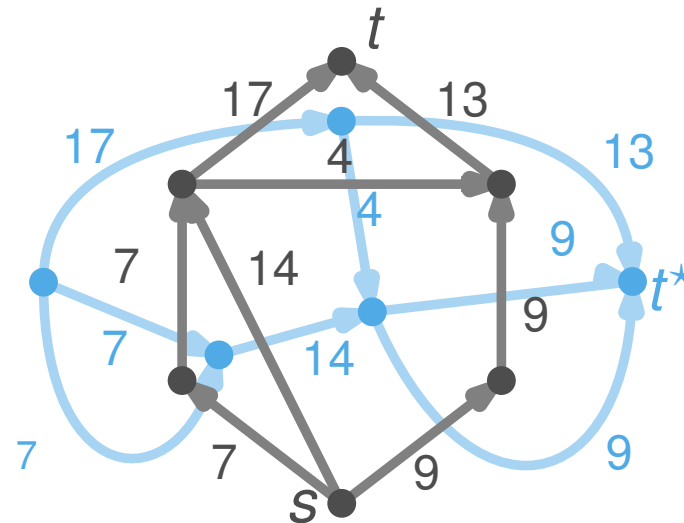
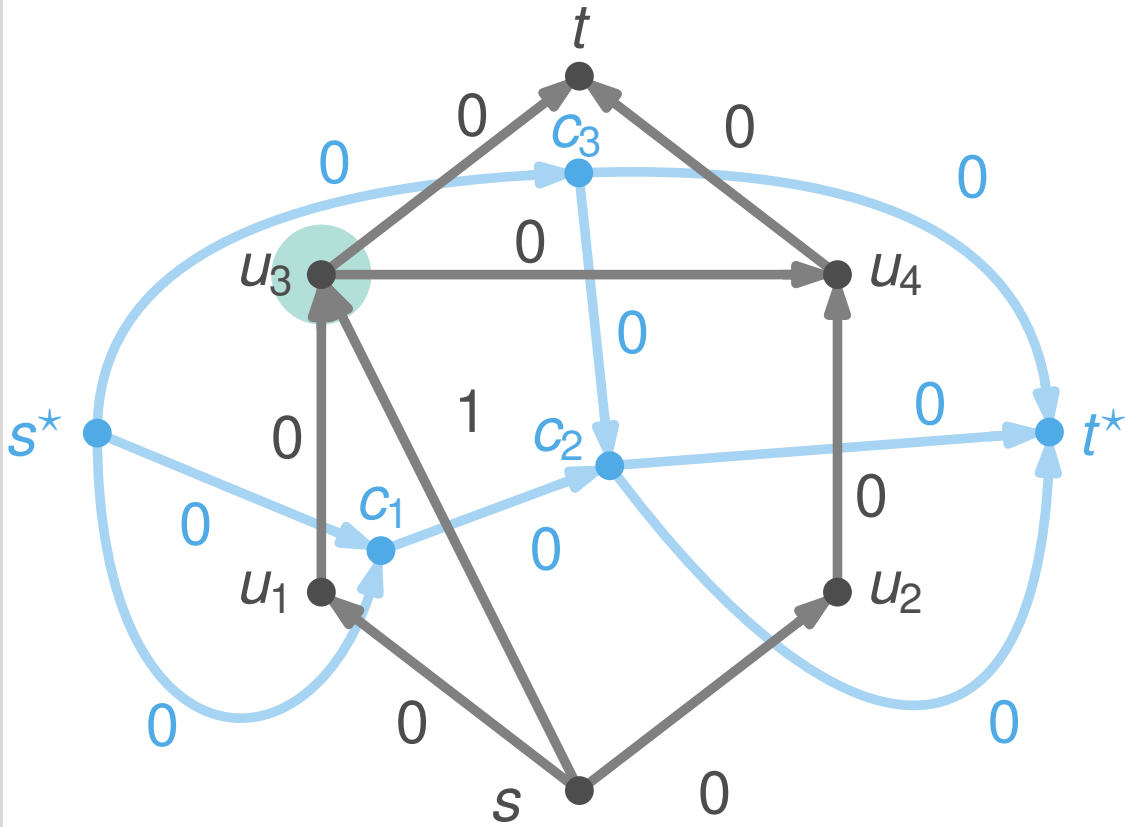
	17	13	
17		13	
		44	9
7	7	14	9
	14		9
7	7		9
			31
			30

# Wrong Conflict Resolution



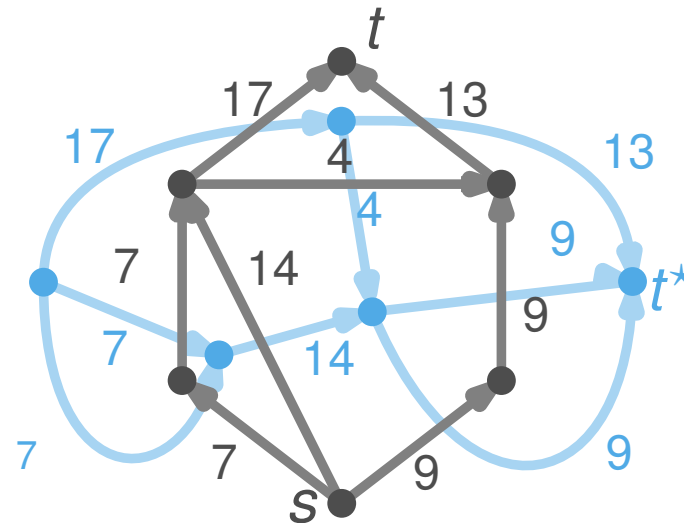
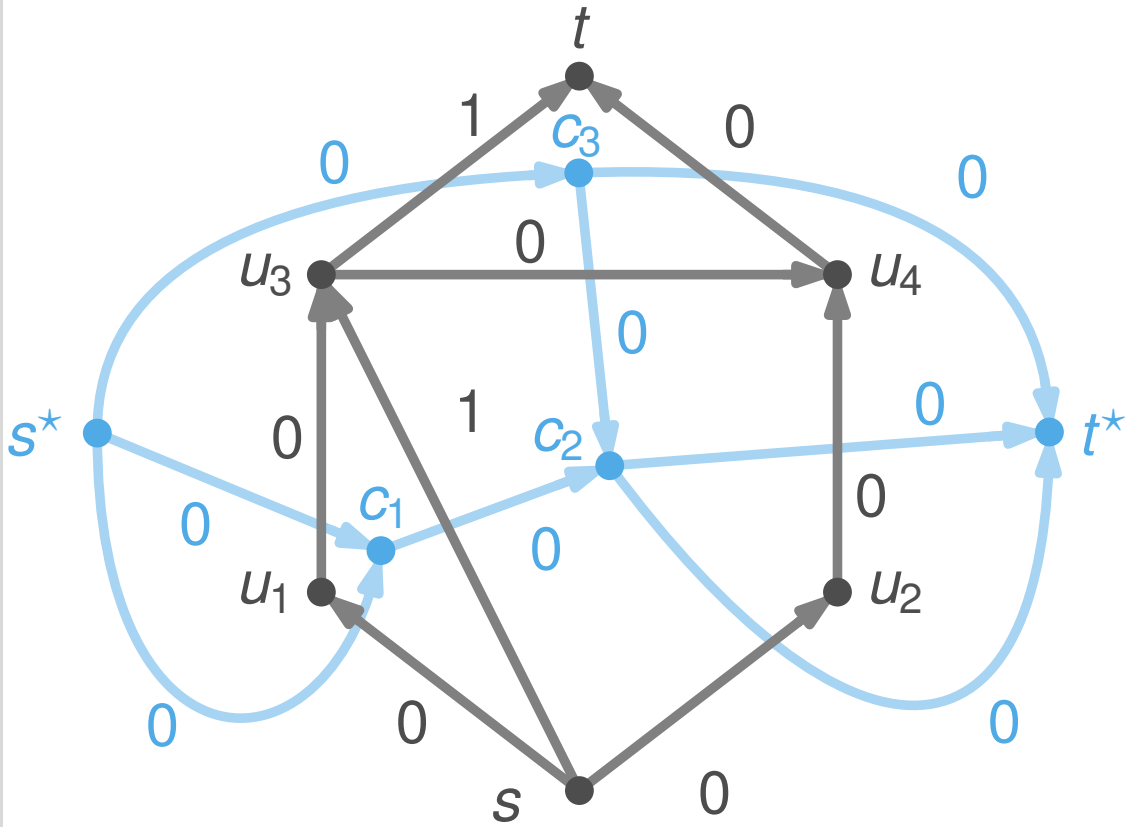
	17	13	
17		13	
		44	9
7	7	14	9
			9
7	7	14	9
			9
			30

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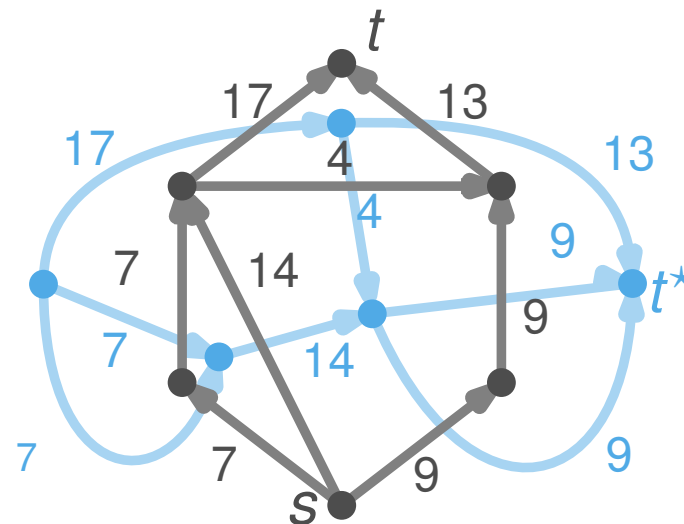
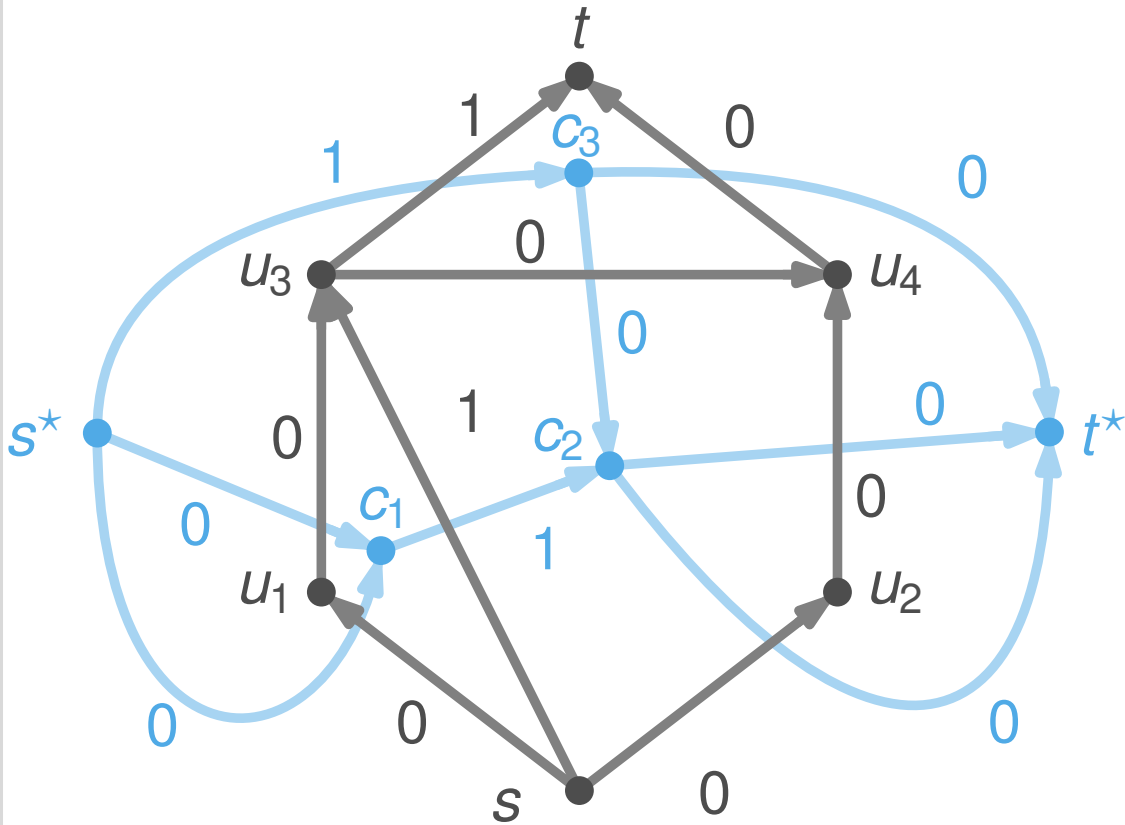
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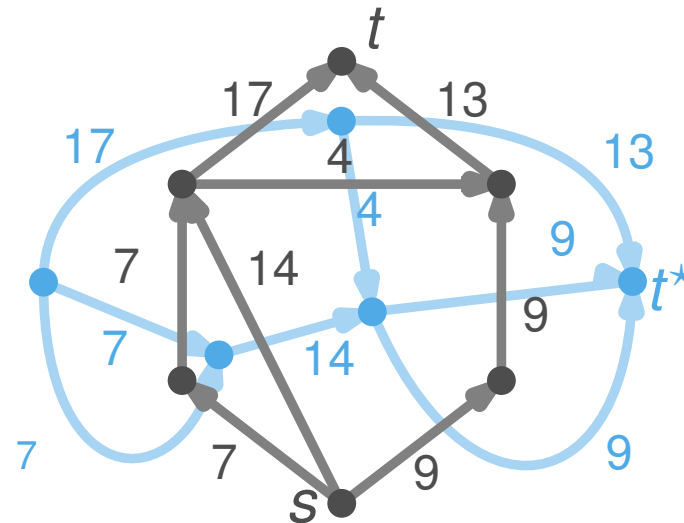
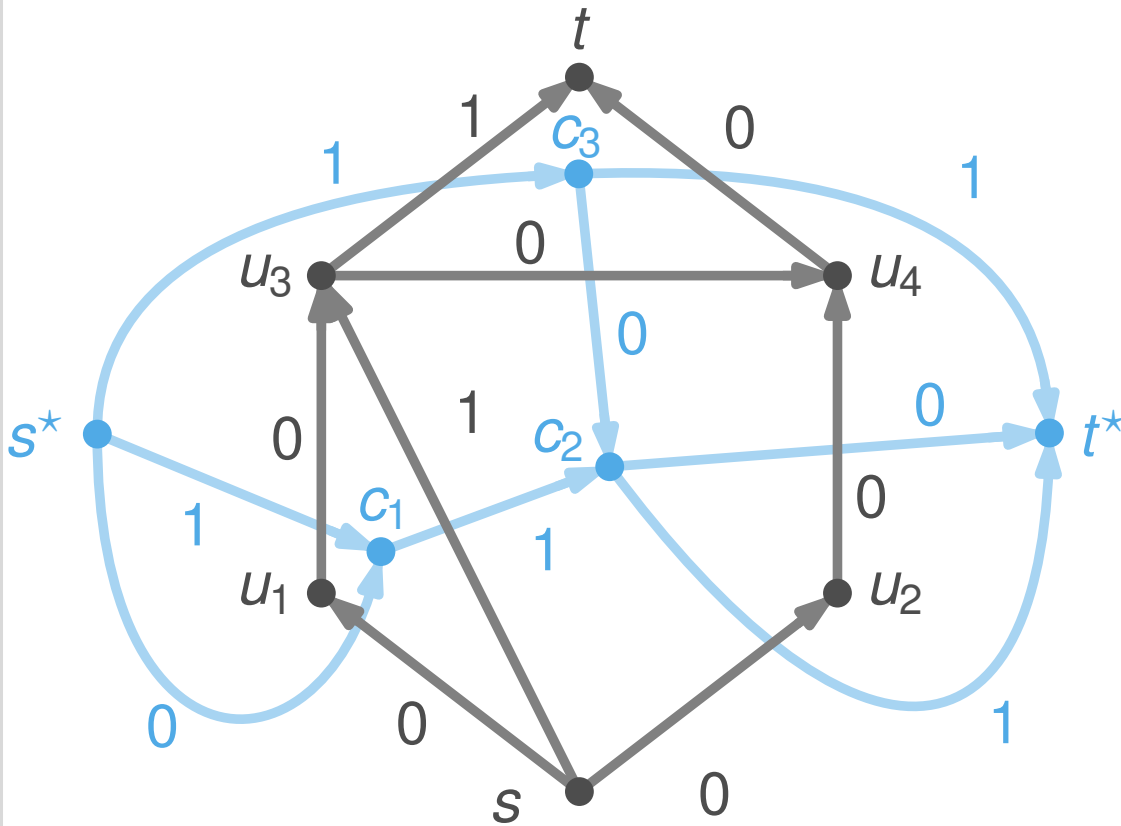
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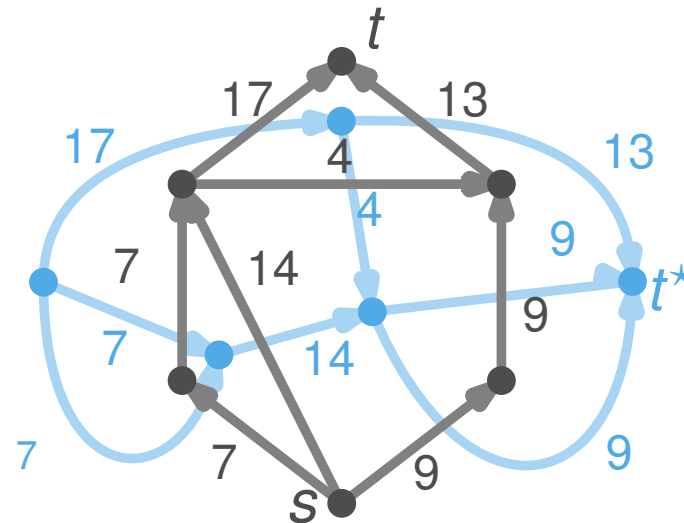
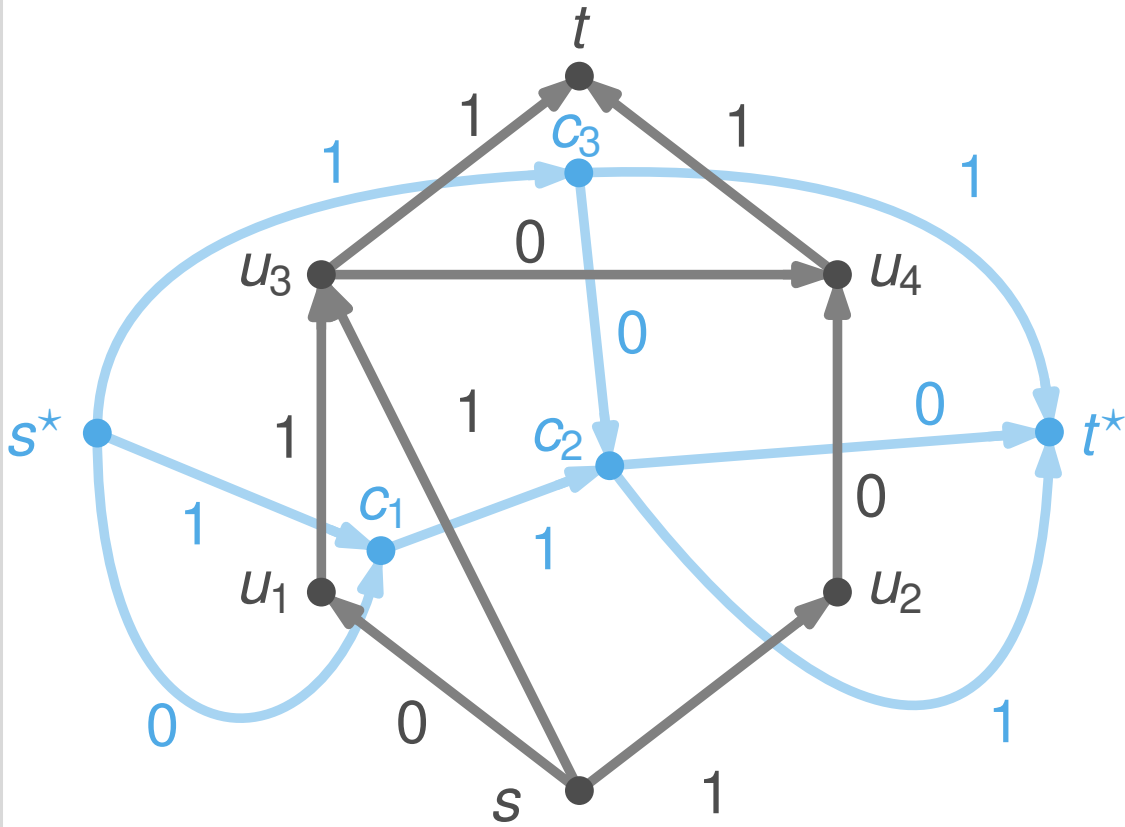
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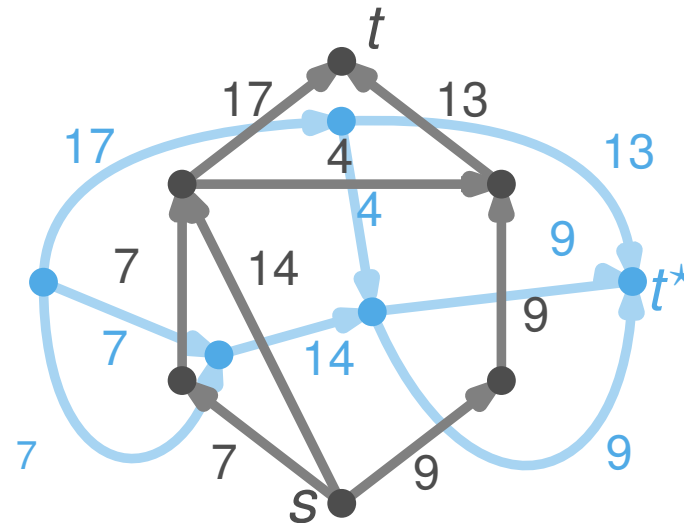
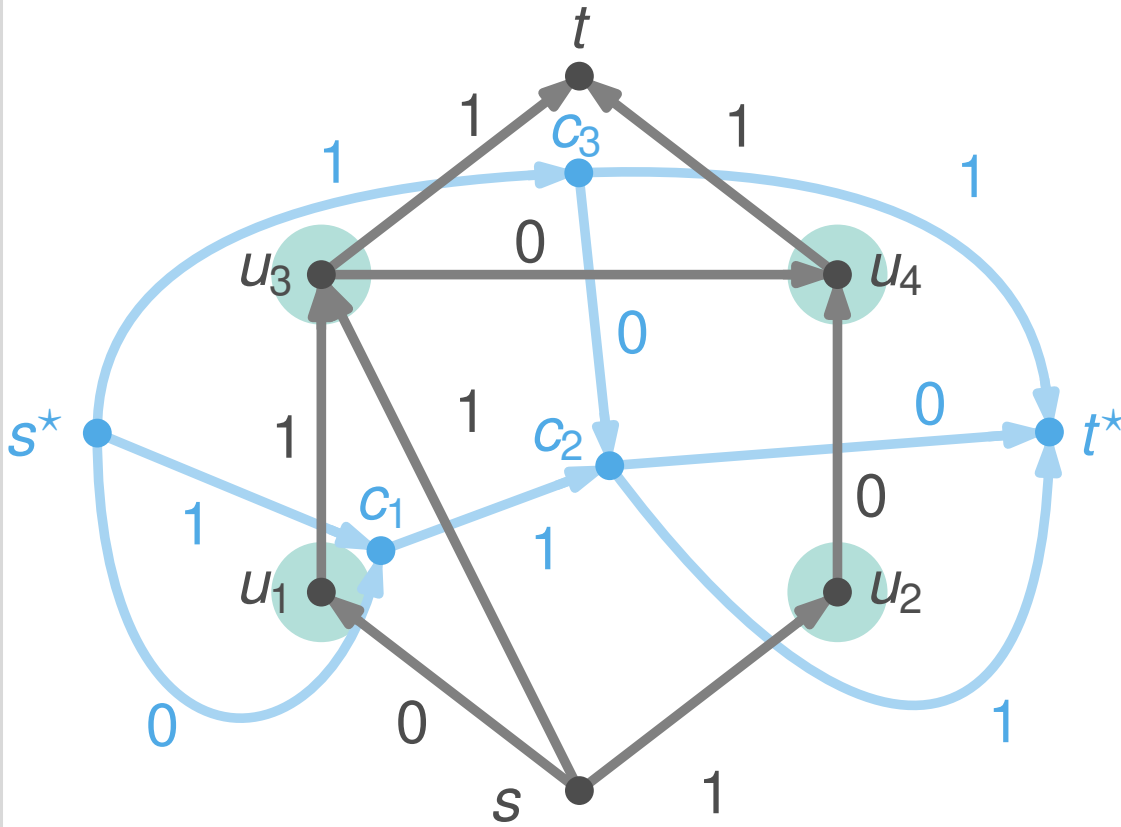
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17		13	
31		44	9
7	7	14	9
7		14	9
30			

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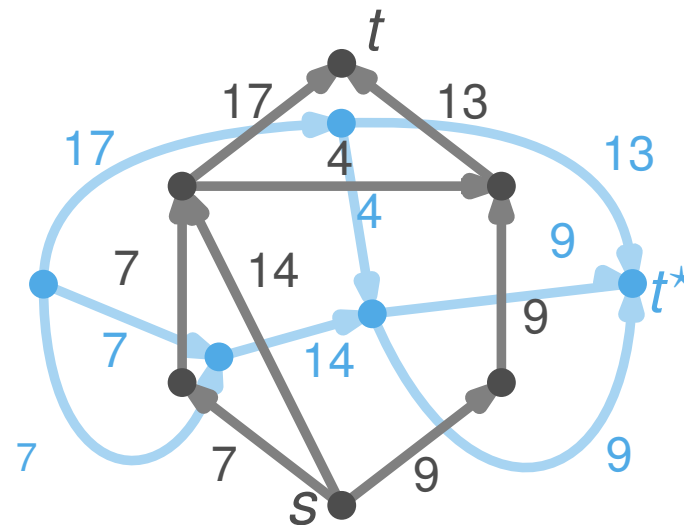
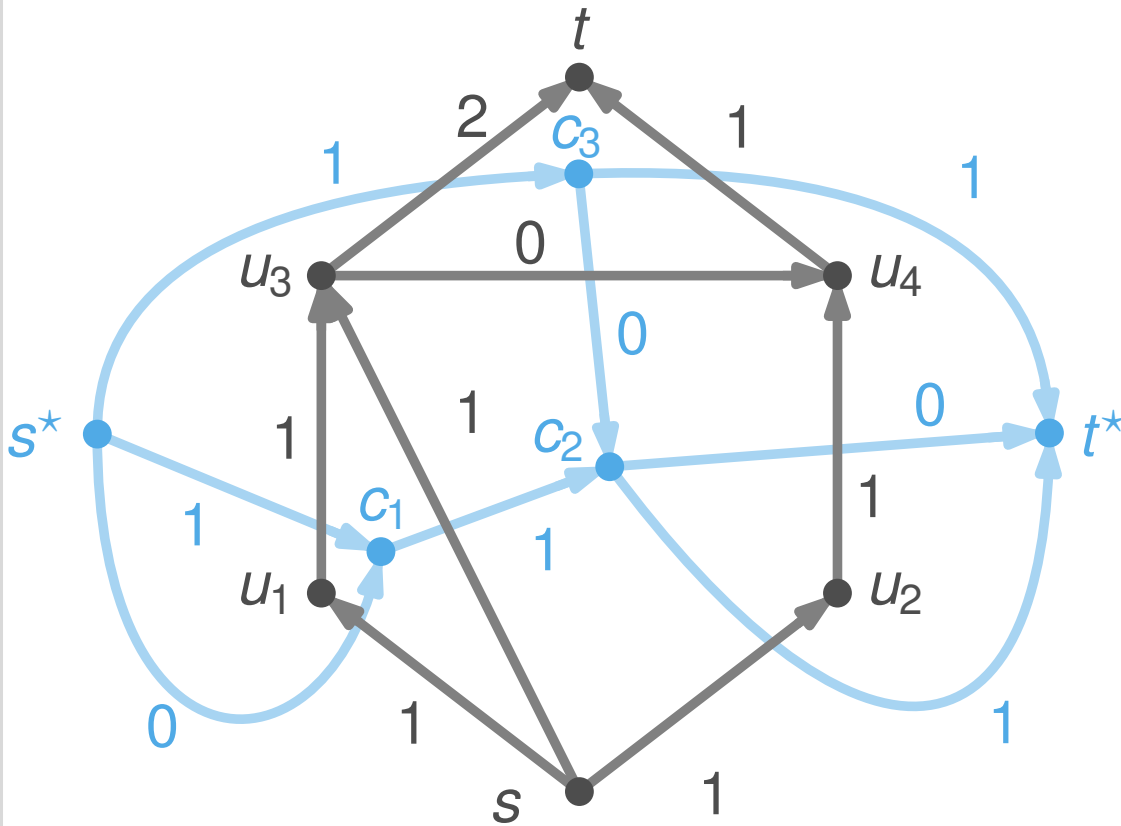
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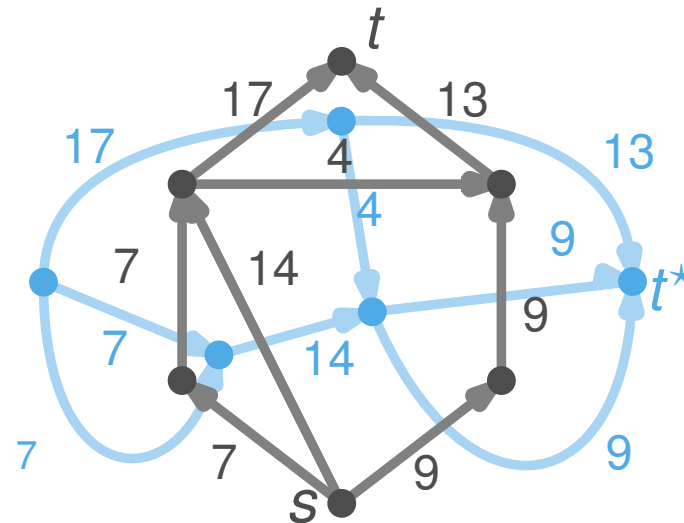
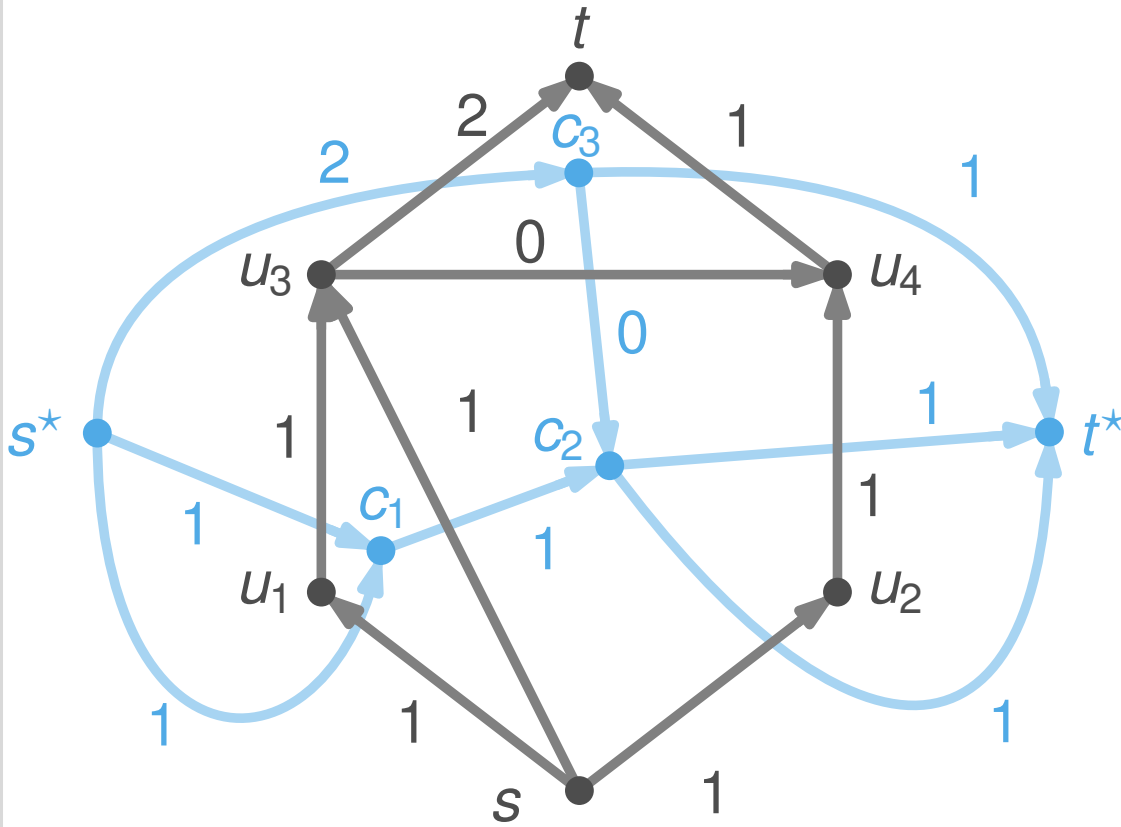


# Wrong Conflict Resolution



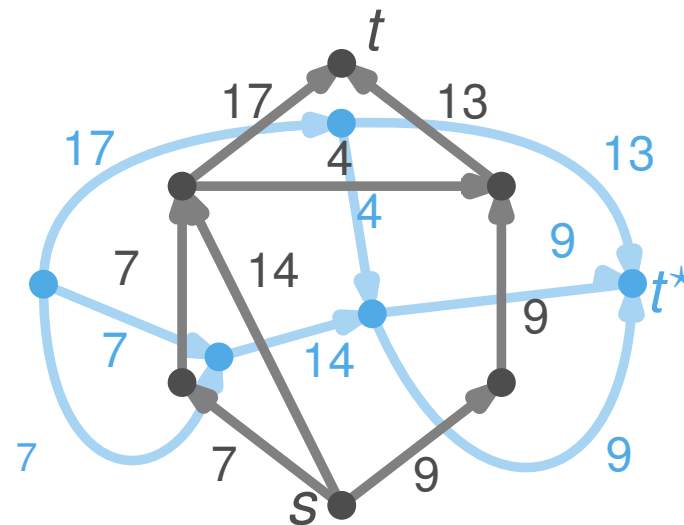
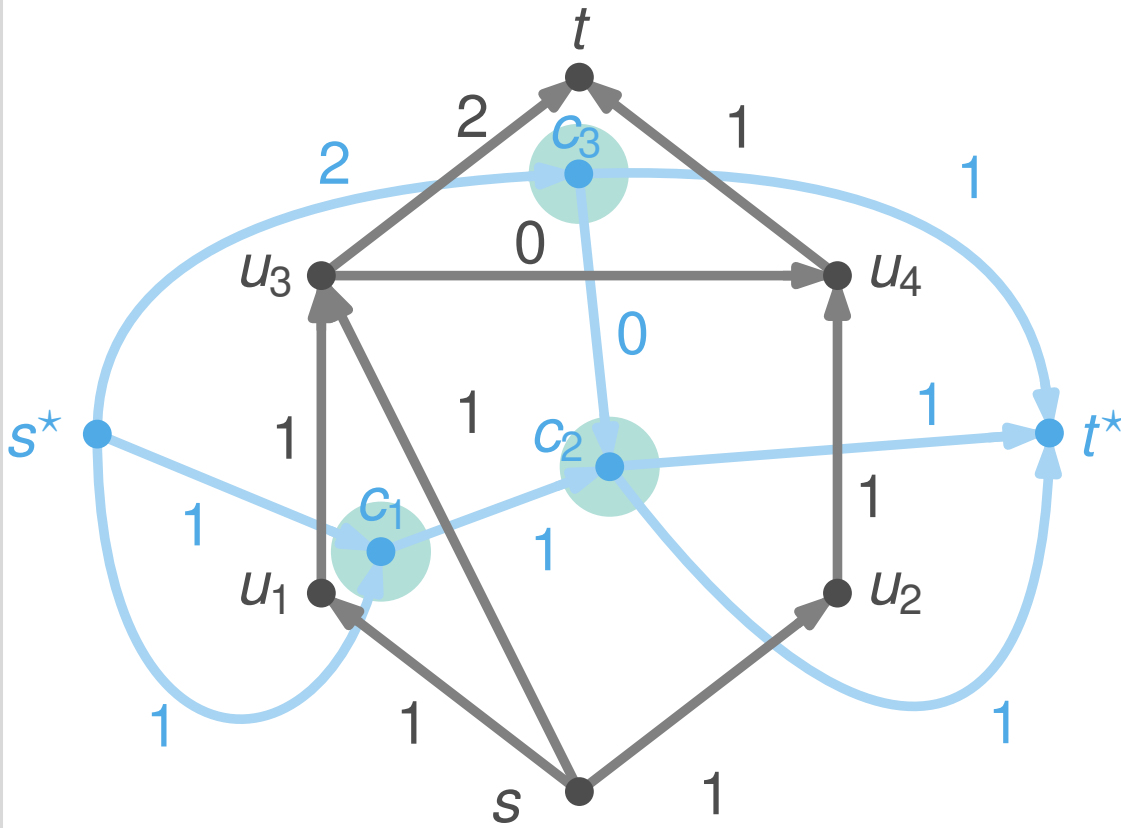
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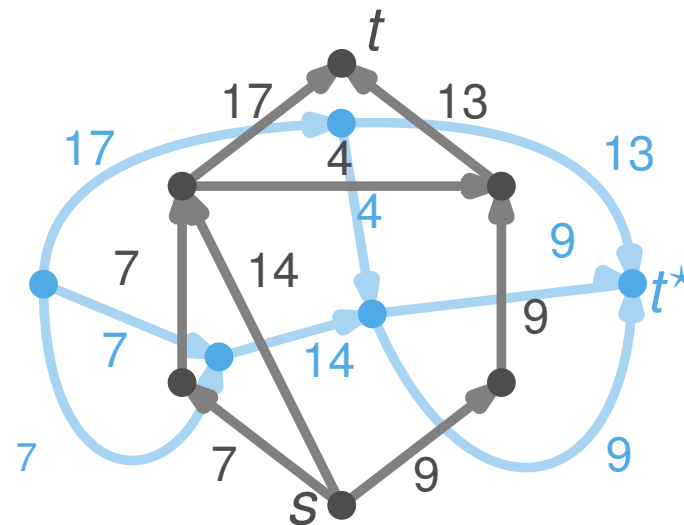
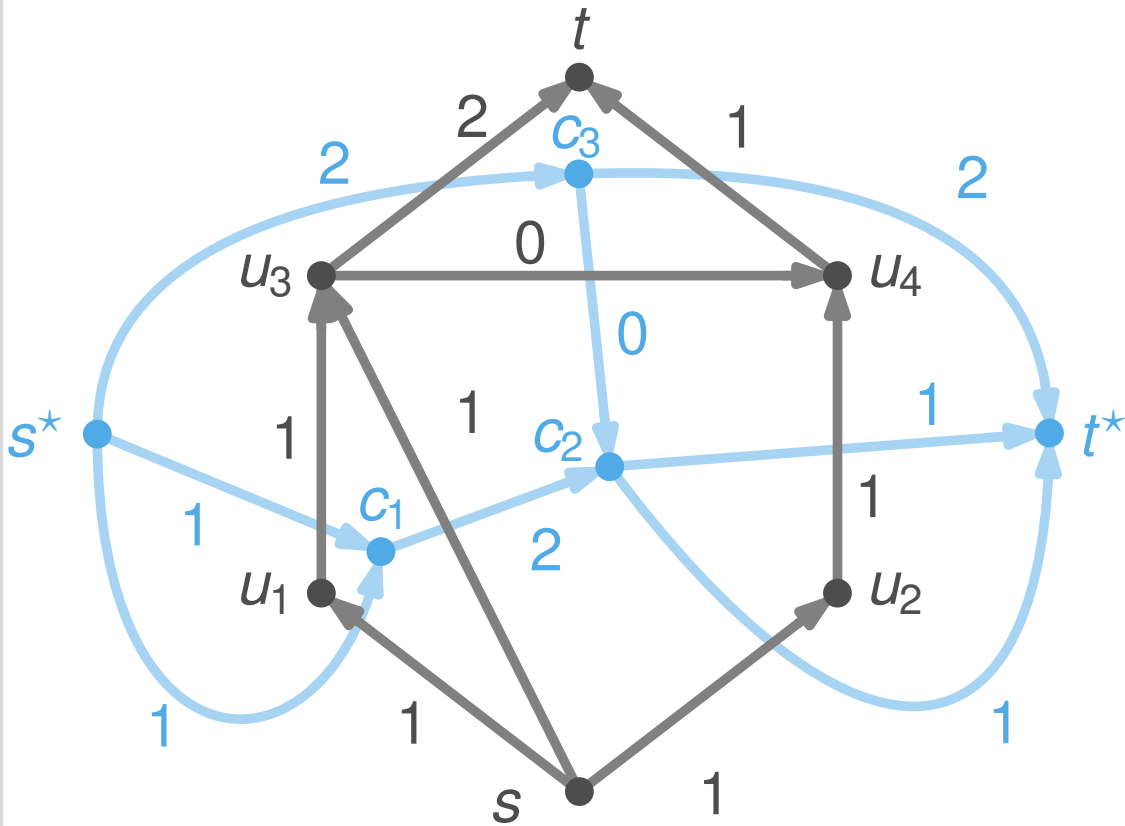
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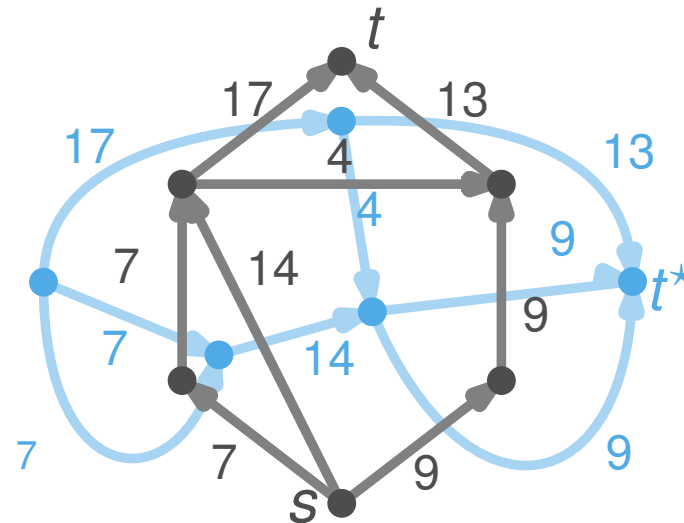
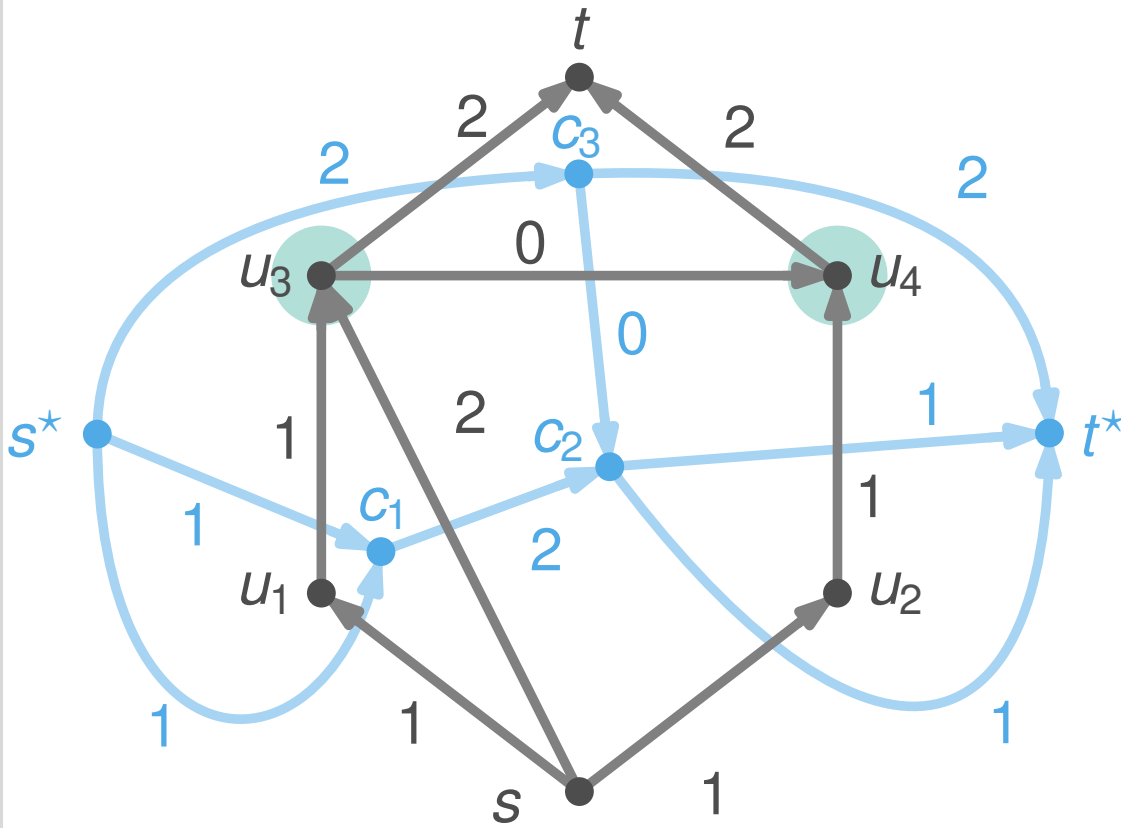
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17		13	
		44	9
7	7	14	9
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7	7		9
			30

# Wrong Conflict Resolution



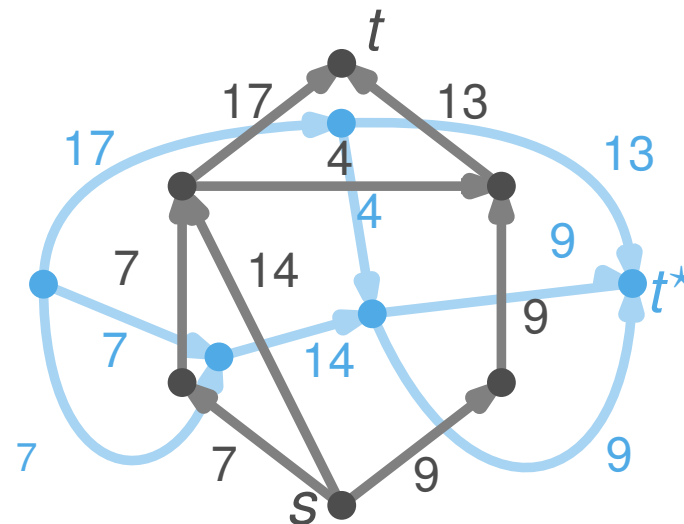
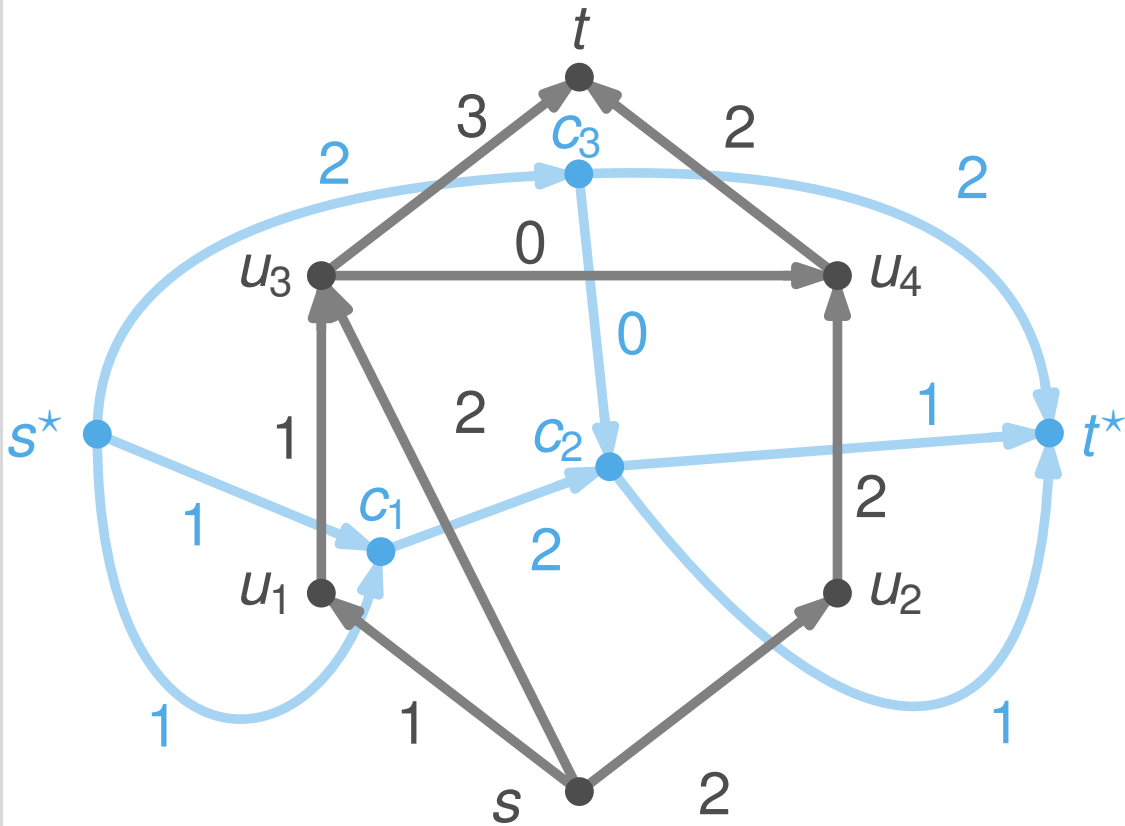
	17	13	
17		13	
		44	9
7	7	14	9
7	7	14	9
			31
			30

# Wrong Conflict Resolution



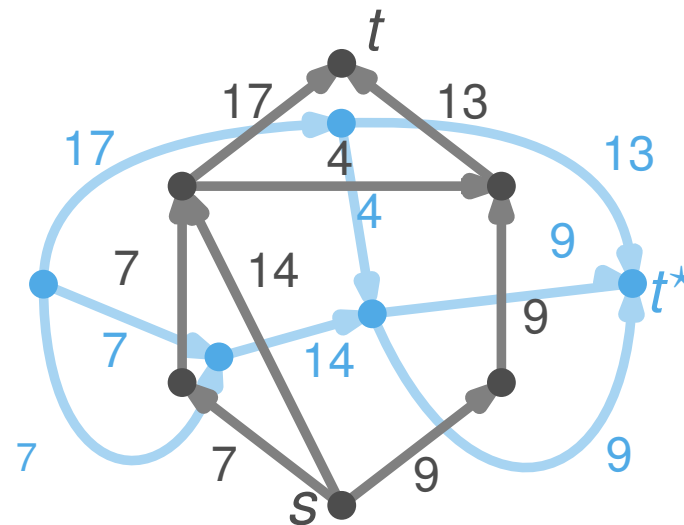
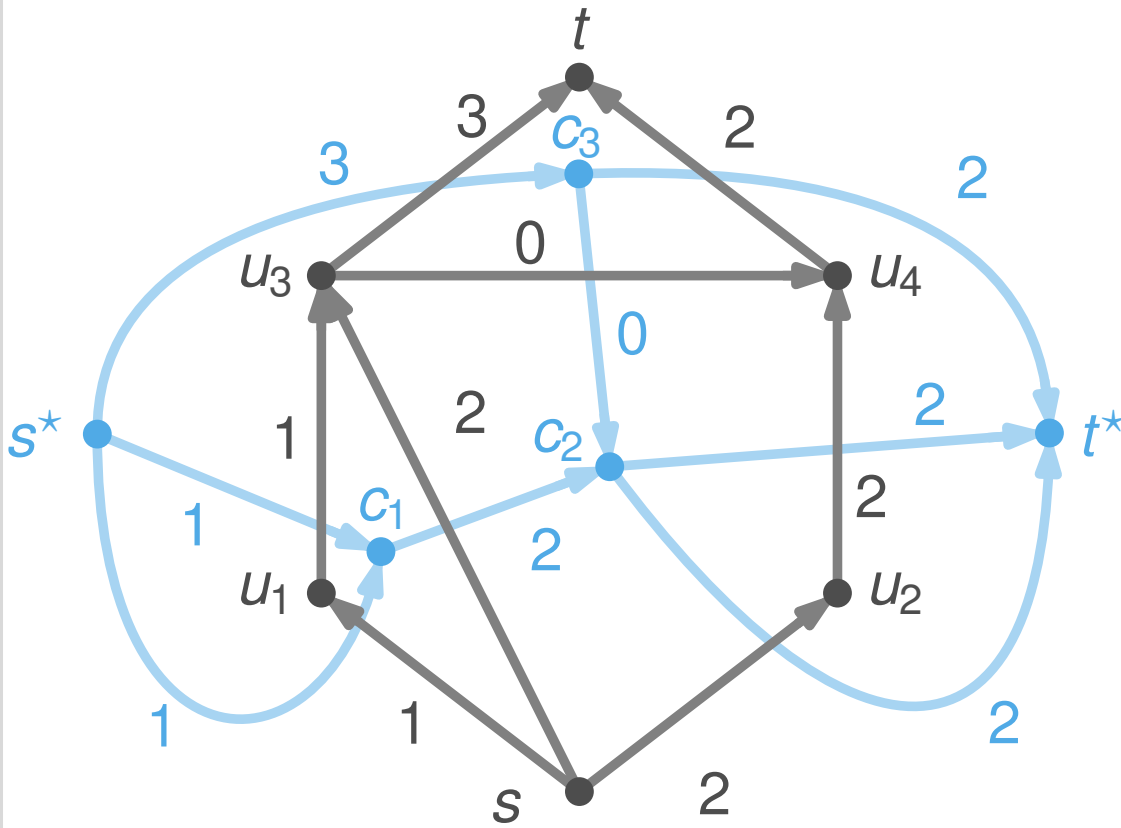
	17	13	
17		13	
		44	9
7	7	14	9
	14		9
7	7		9
			30

# Wrong Conflict Resolution



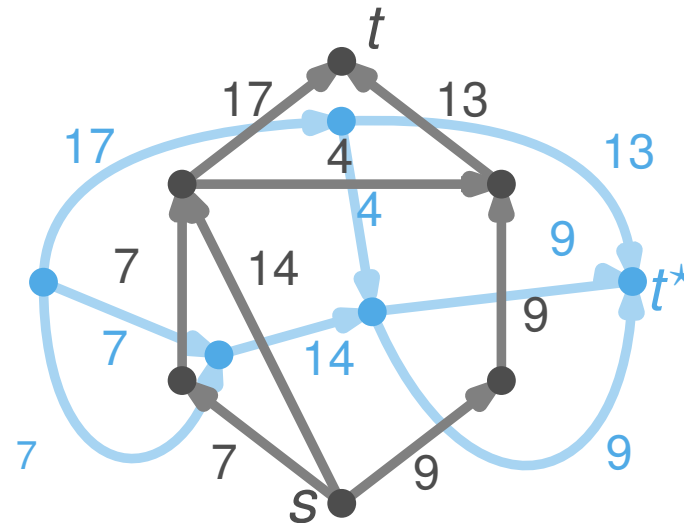
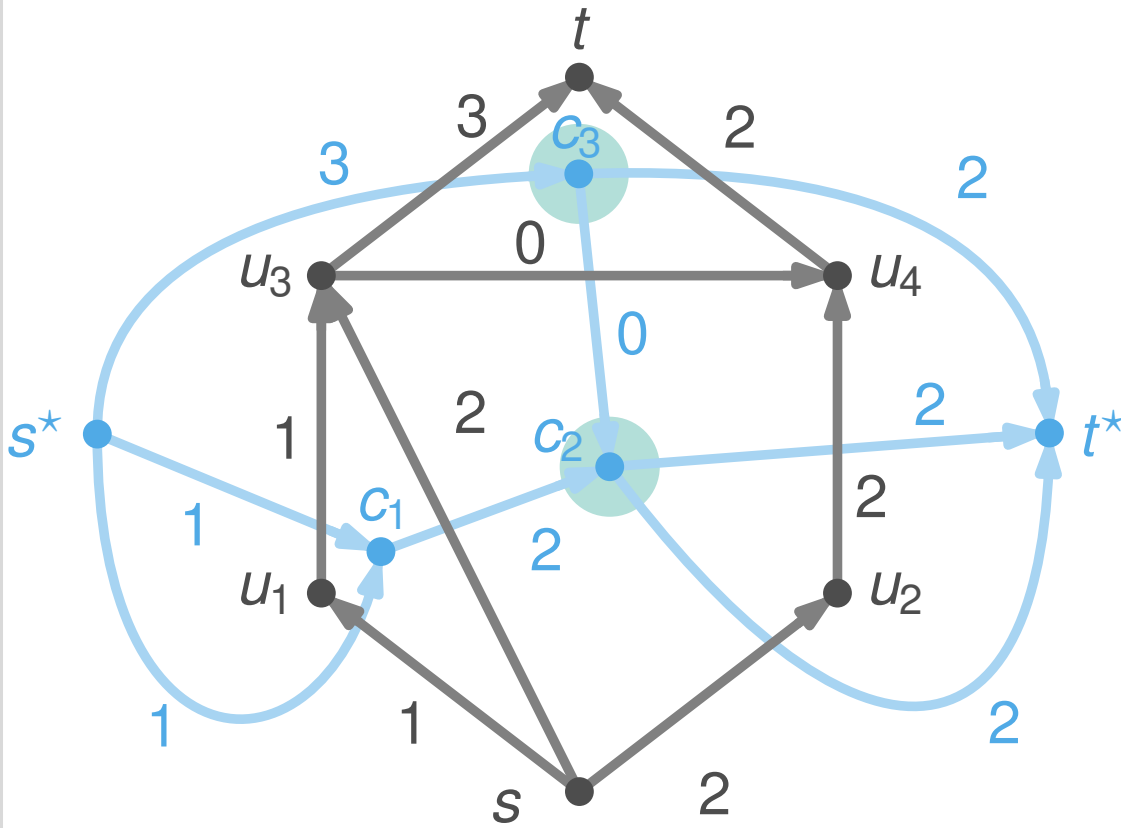
	17	13	
17		13	
		44	9
7	7	14	9
	14		9
7	7		9
			30

# Wrong Conflict Resolution



	17	13	
17		13	
		44	9
7	7	14	9
	14		9
7	7		9
			30

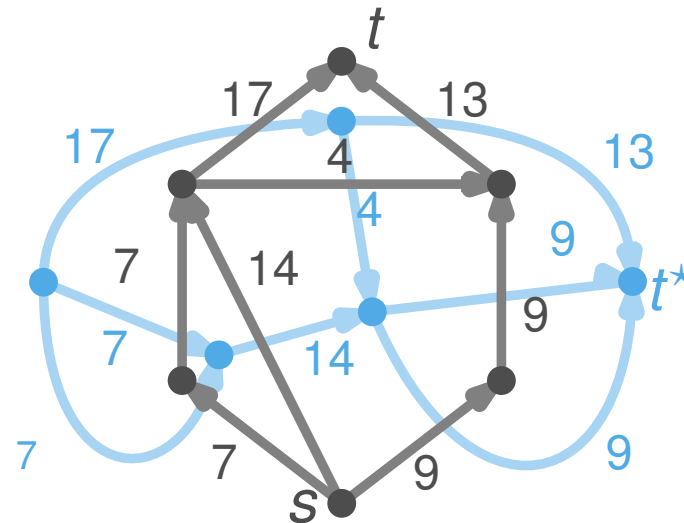
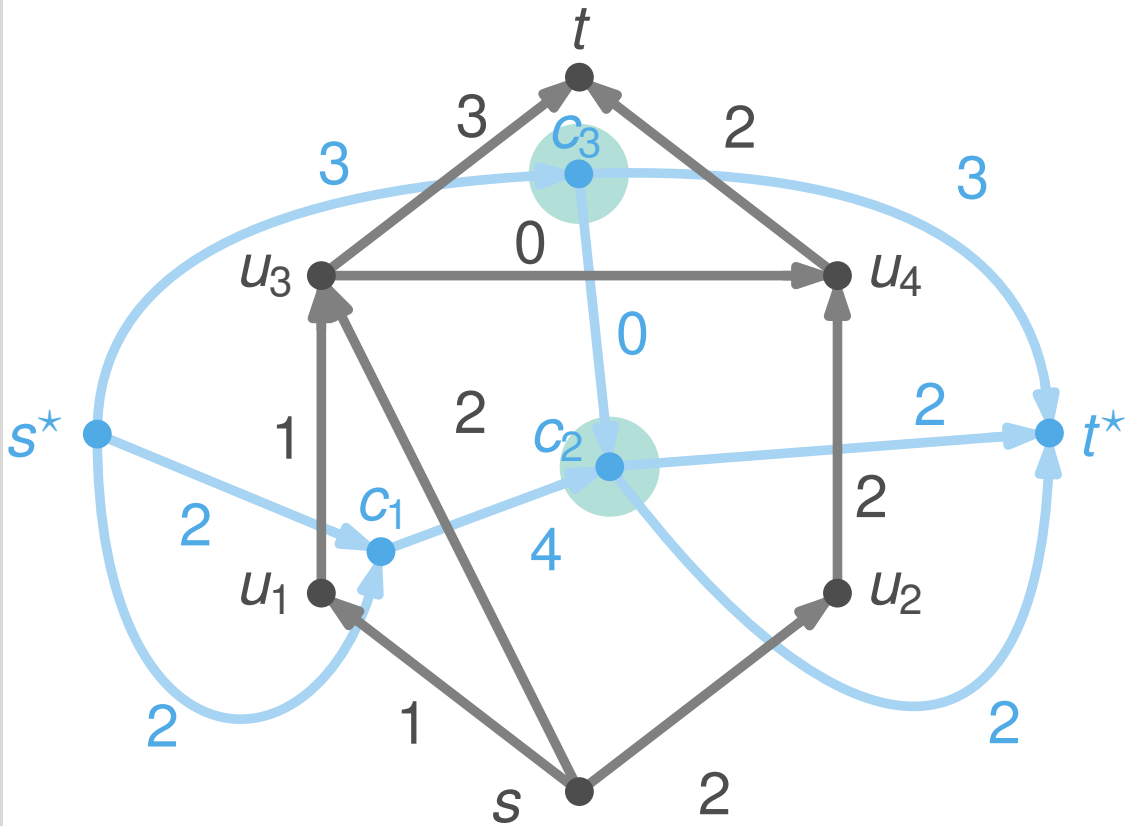
# Wrong Conflict Resolution



	17	13	
17		13	
		44	9
7	7	14	9
	14		9
7	7		9
			31
			30

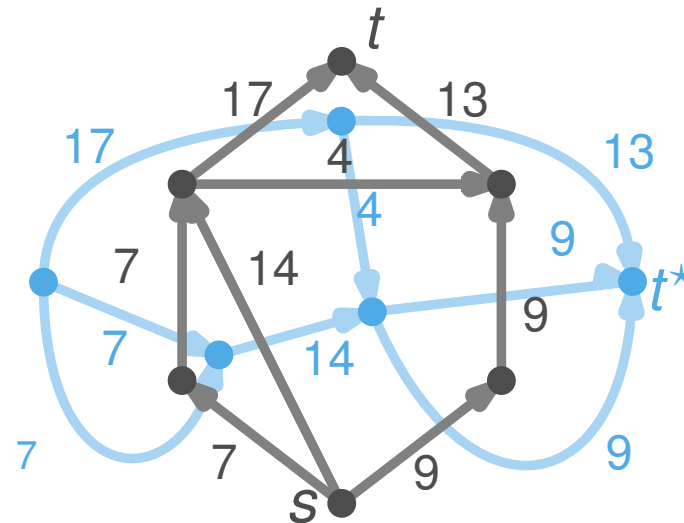
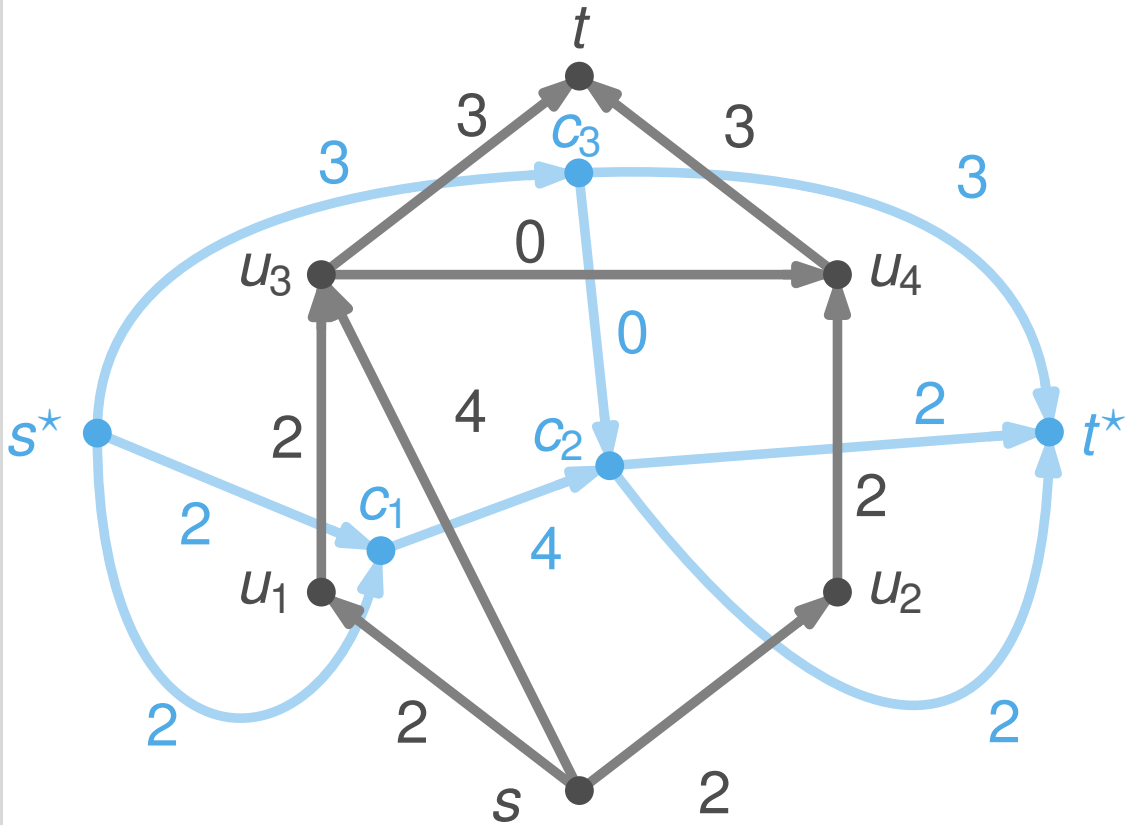


# Wrong Conflict Resolution



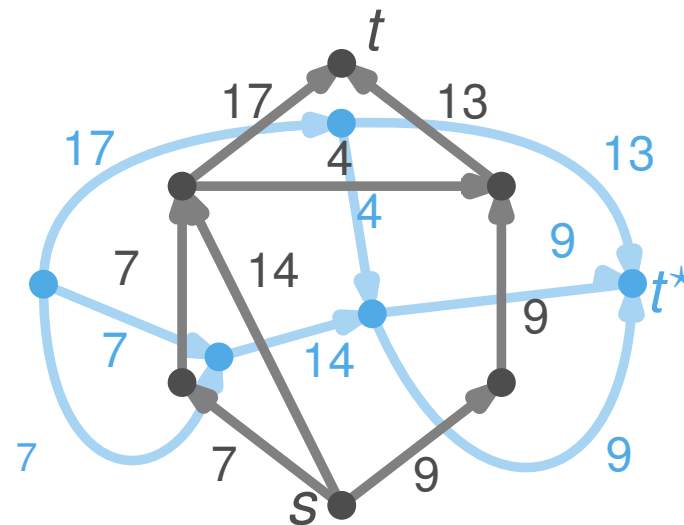
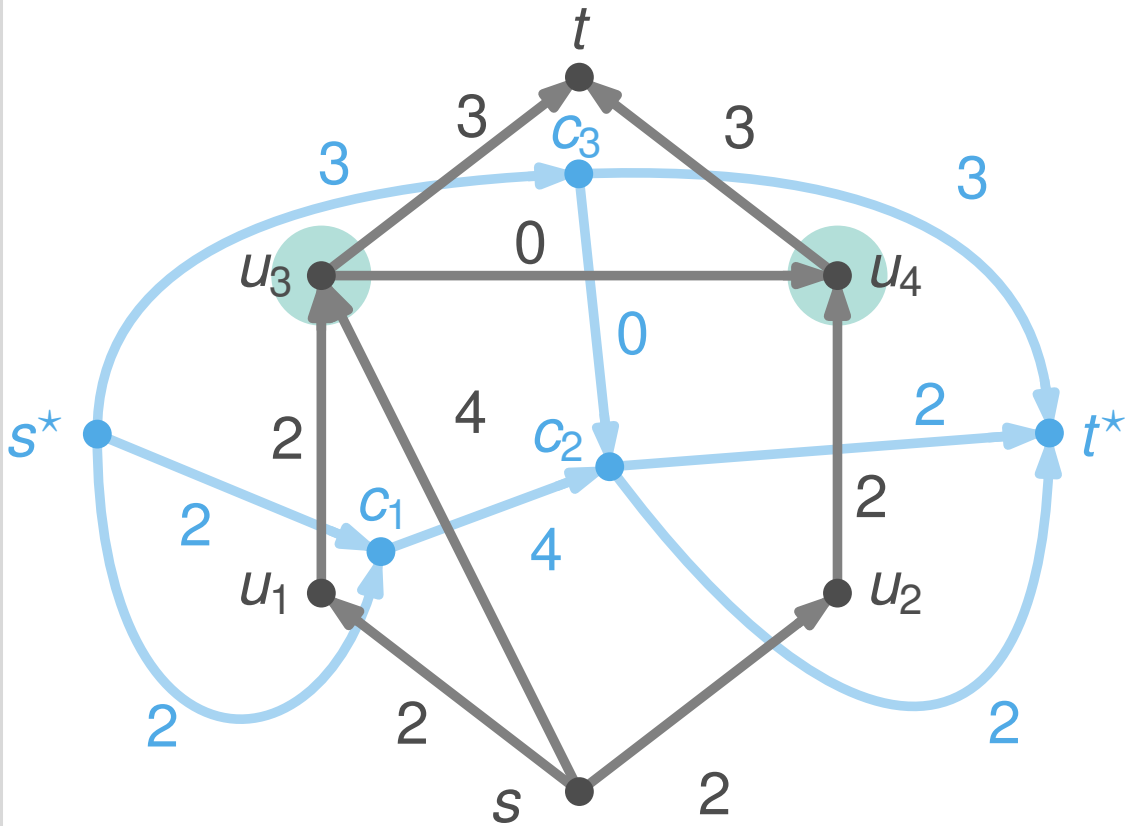
	17	13	
17		13	
		44	9
7	7	14	9
	14		9
7	7		9
			31
			30

# Wrong Conflict Resolution



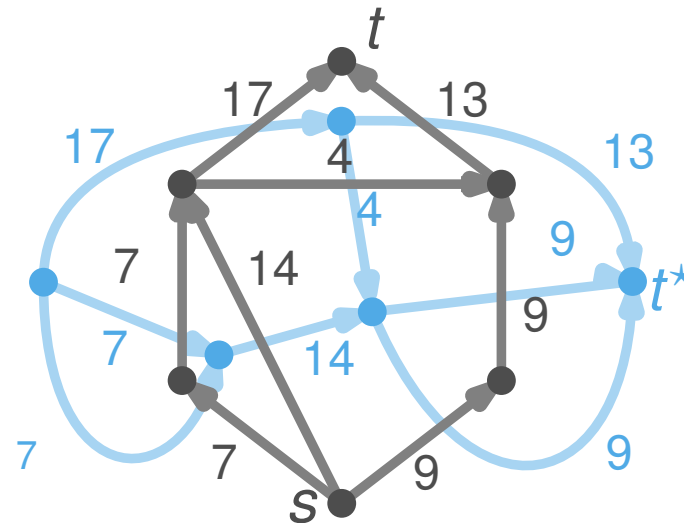
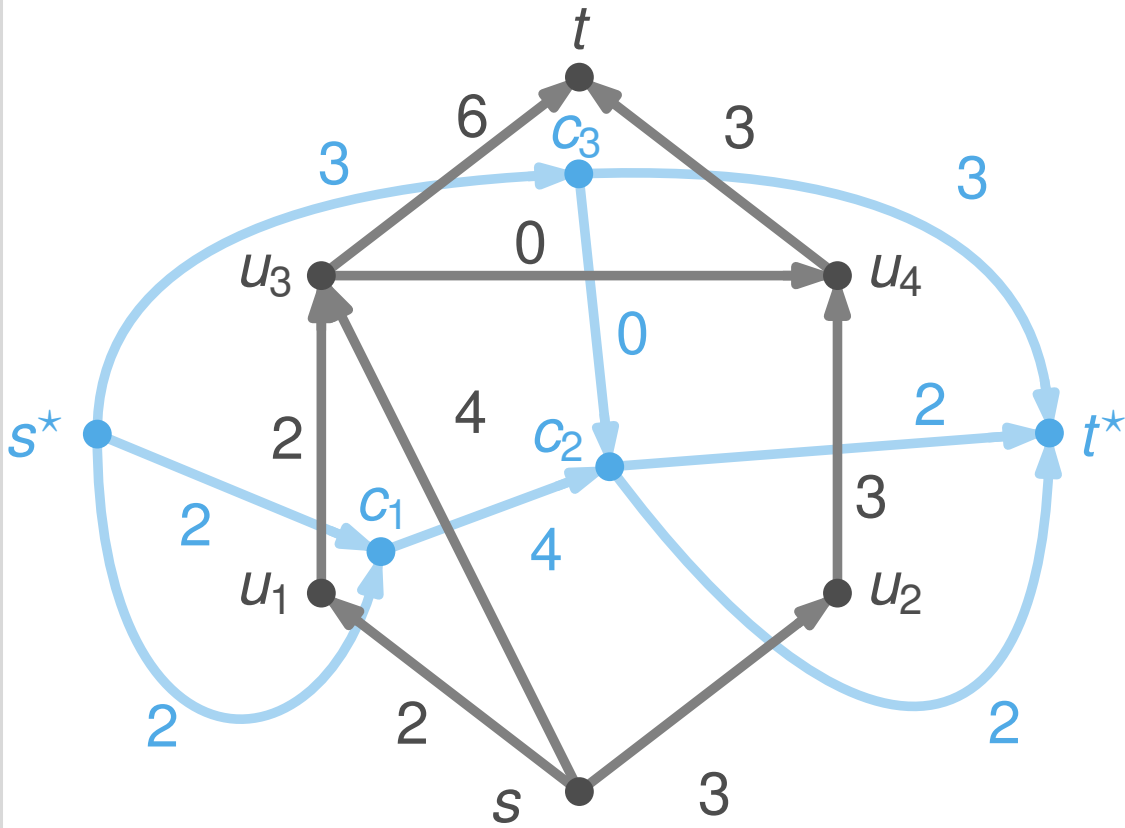
	17	13	
17		13	
		44	9
7	7	14	9
	14		9
7	7		9
			30
			31

# Wrong Conflict Resolution



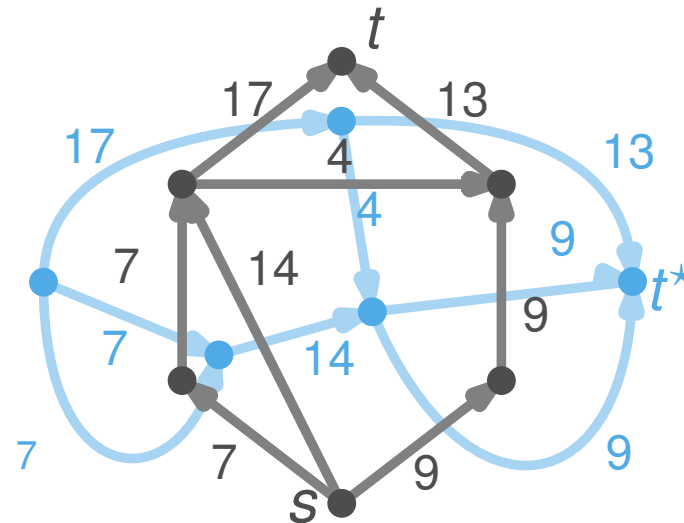
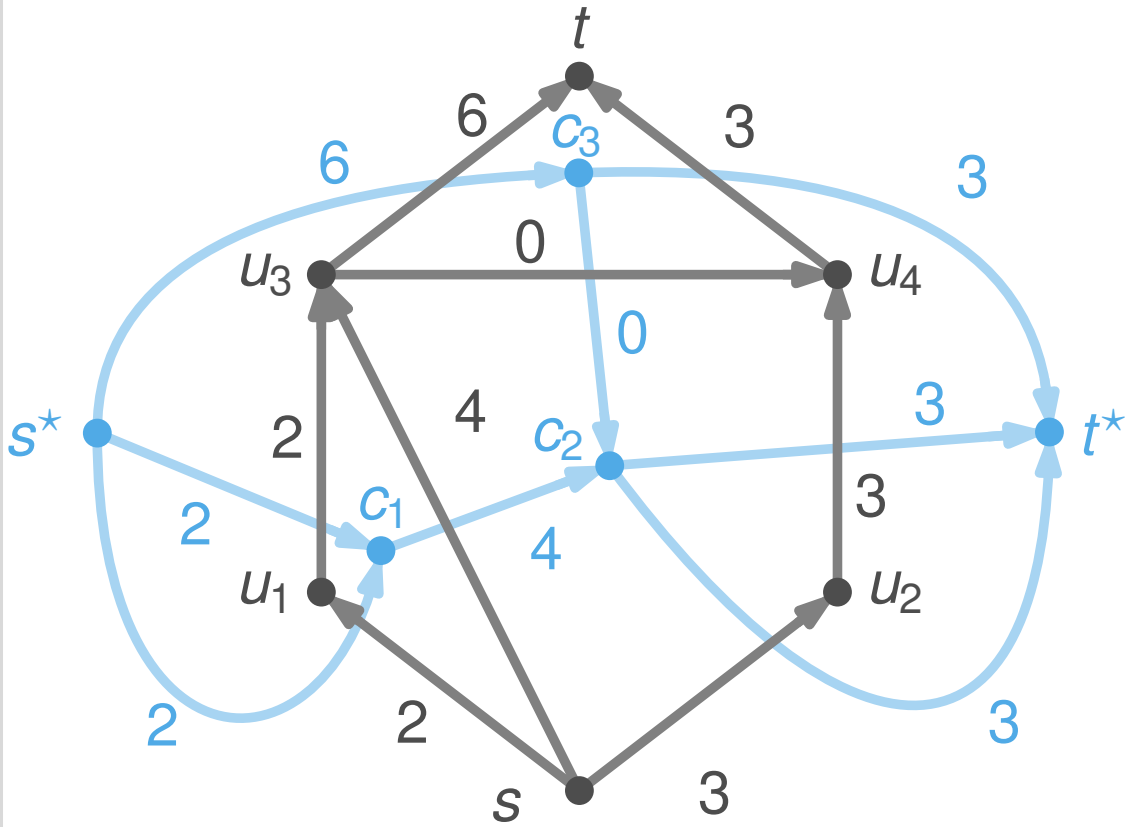
	17	13	
17		13	
		44	9
7	7	14	9
	14		9
7	7		9
			31
			30

# Wrong Conflict Resolution



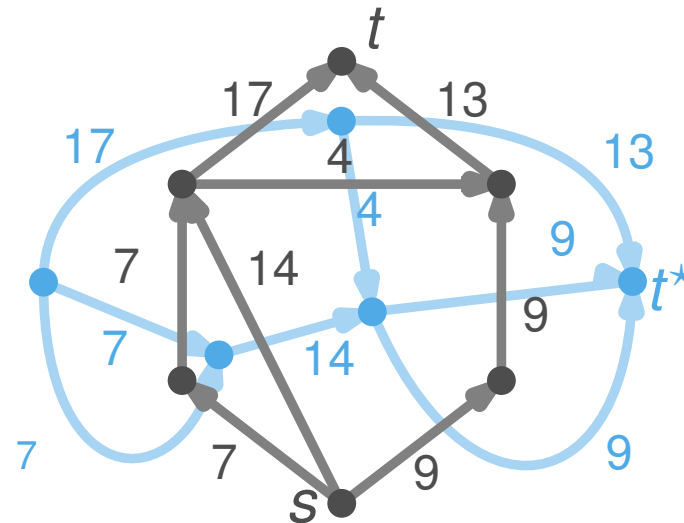
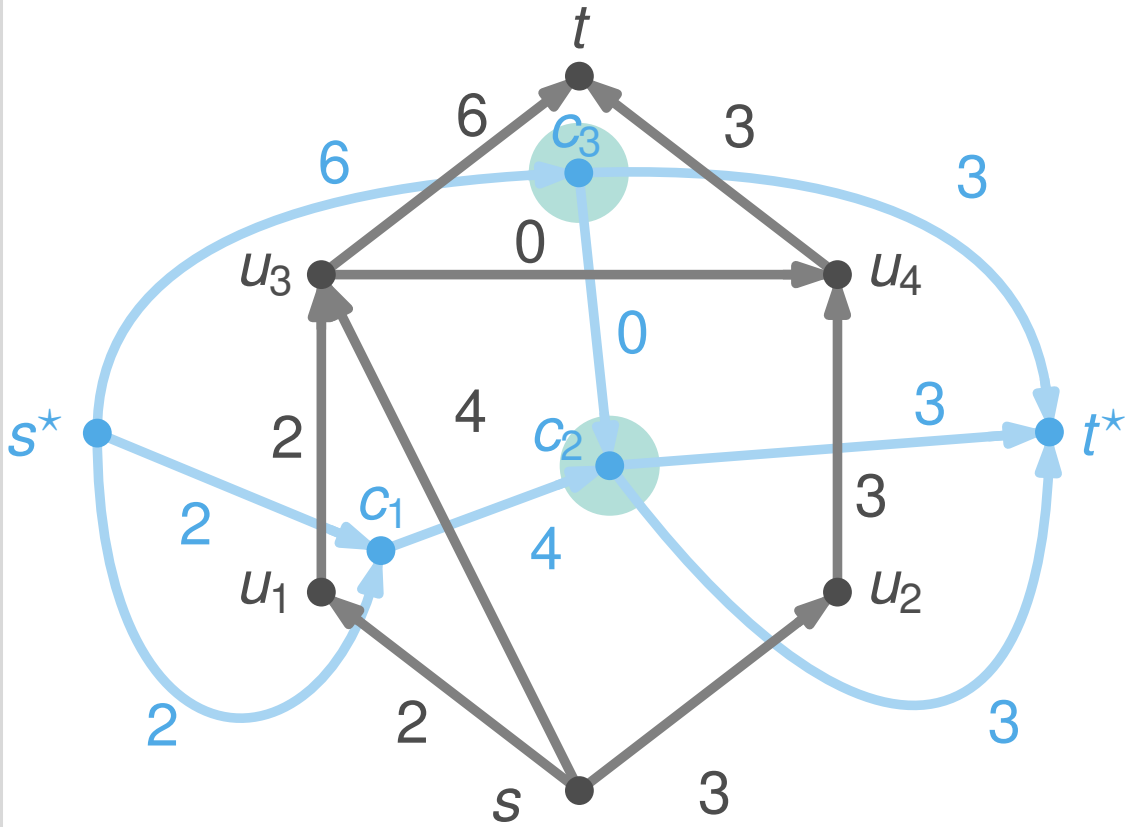
	17	13	
17		13	
		44	9
7	7	14	9
7	7	14	9
31			
			30

# Wrong Conflict Resolution



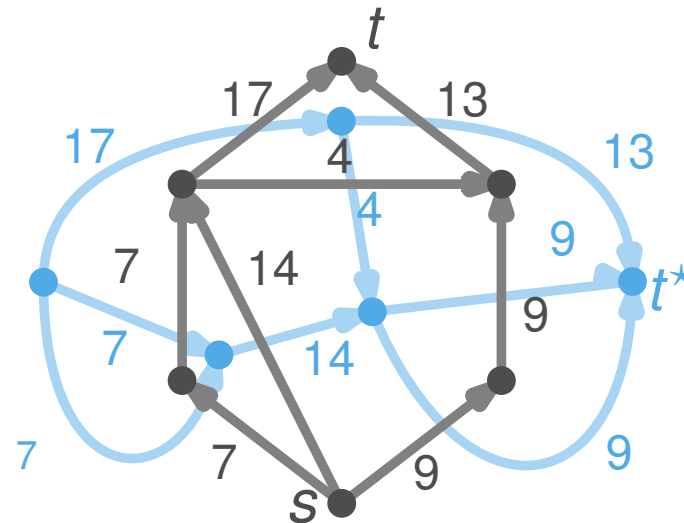
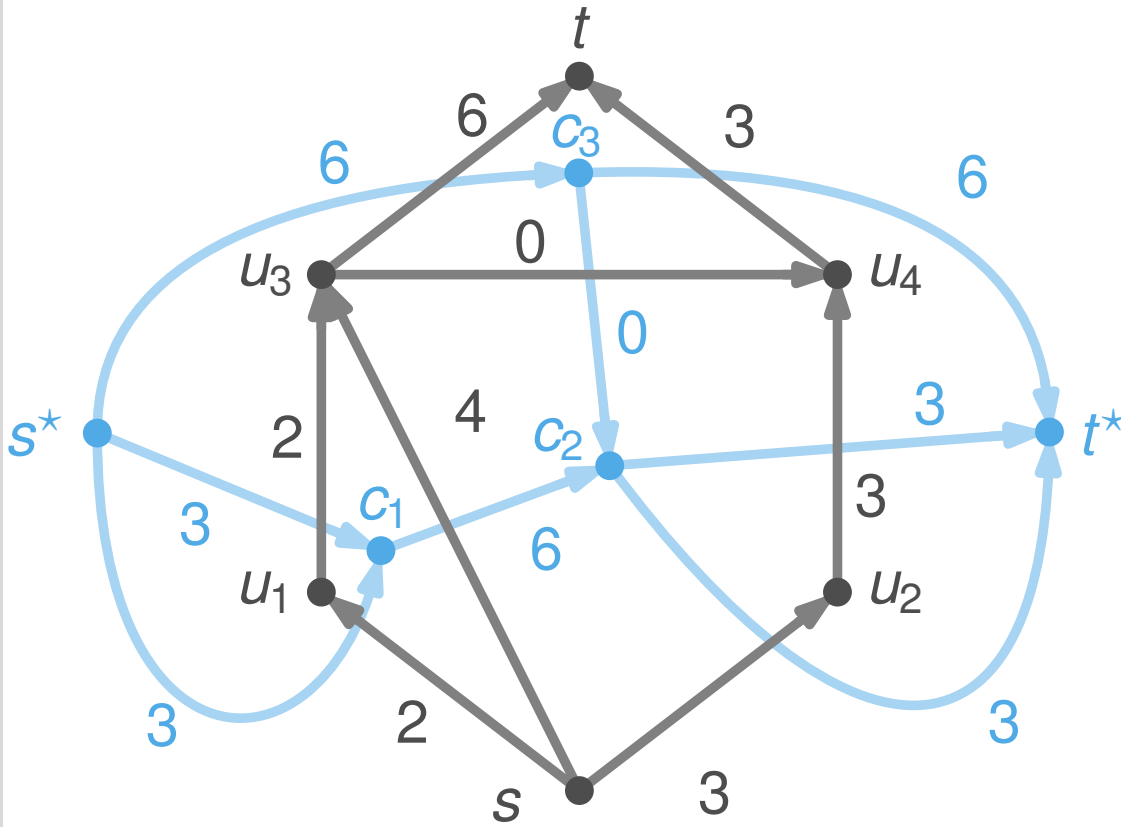
	17	13	
17		13	
		44	9
7	7	14	9
	14		9
7	7		9
			30

# Wrong Conflict Resolution



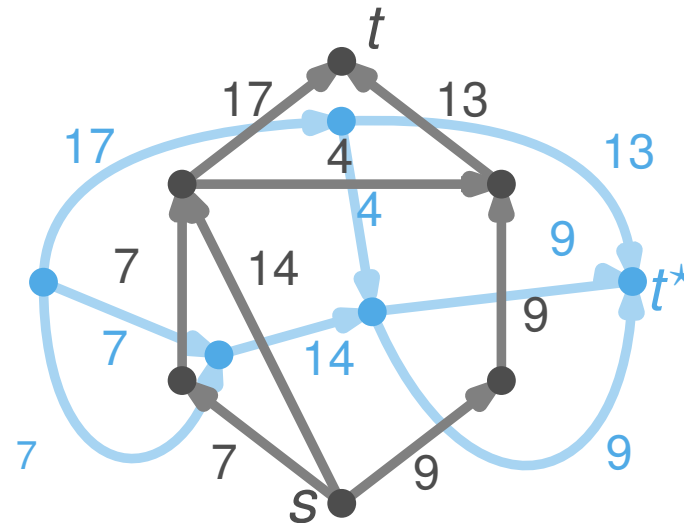
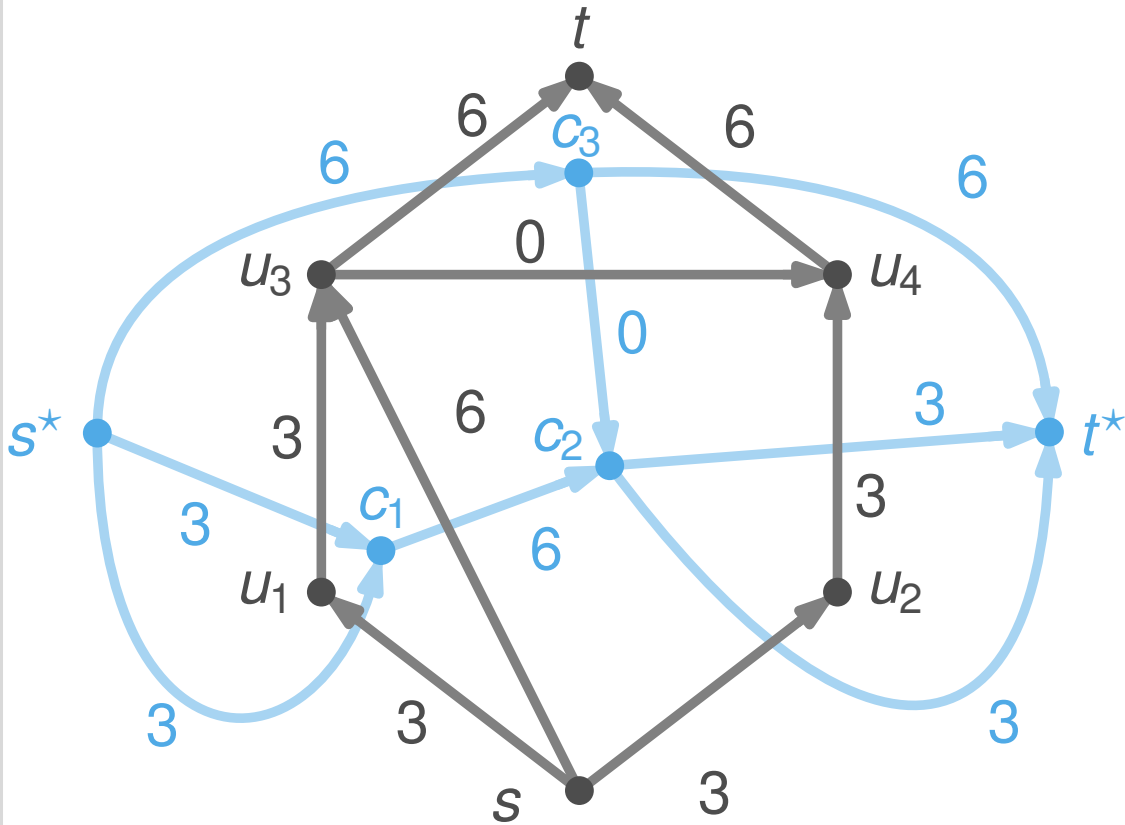
	17	13	
17		13	
		44	9
7	7	14	9
	14		9
7	7		9
			30

# Wrong Conflict Resolution



	17	13	
17		13	
		44	9
7	7	14	9
	14		9
7	7		9
			30

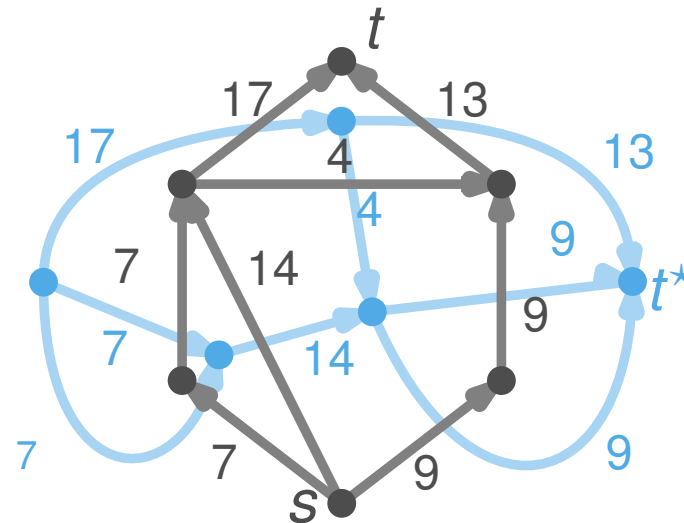
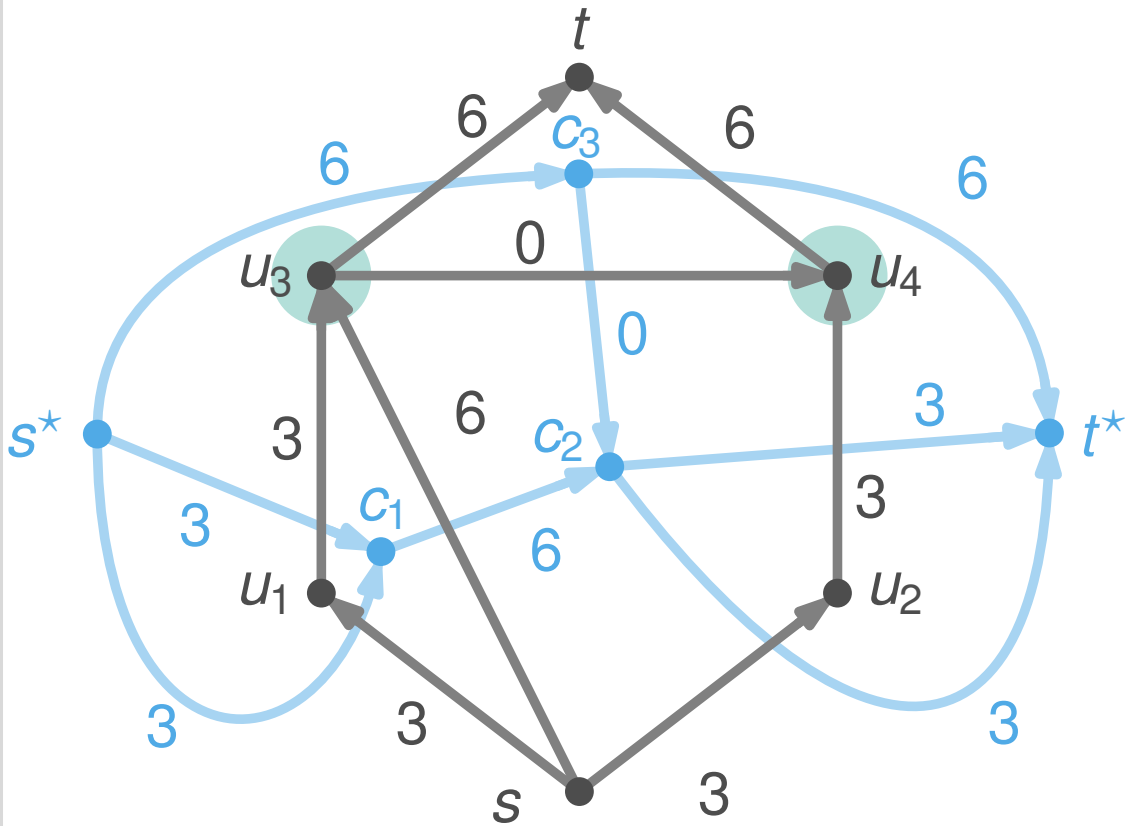
# Wrong Conflict Resolution



	17	13	
17		13	
		44	9
7	7	14	9
	14		9
7	7		9
			30

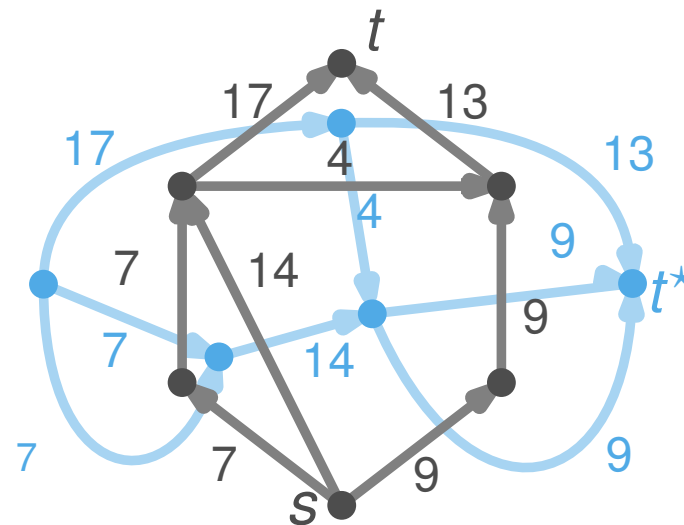
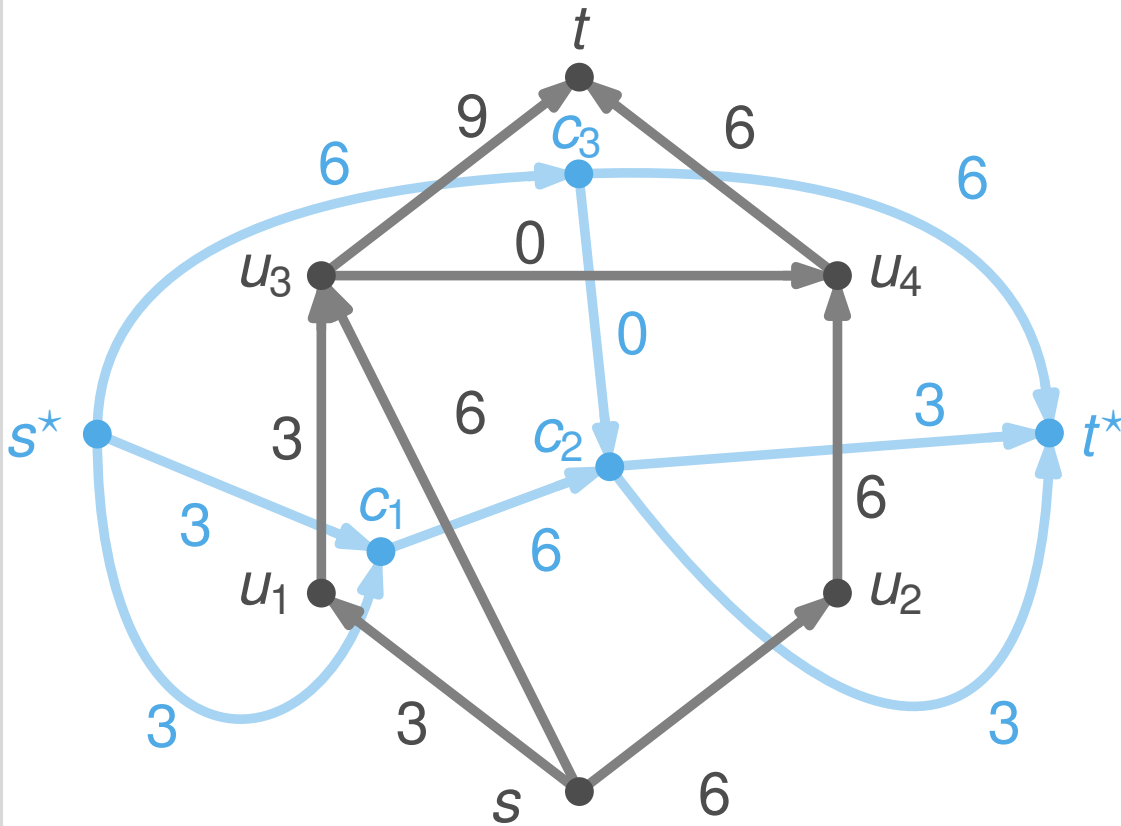


# Wrong Conflict Resolution



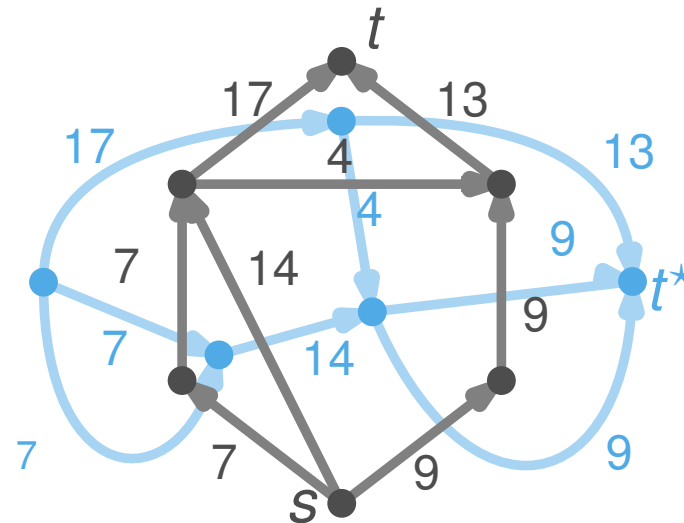
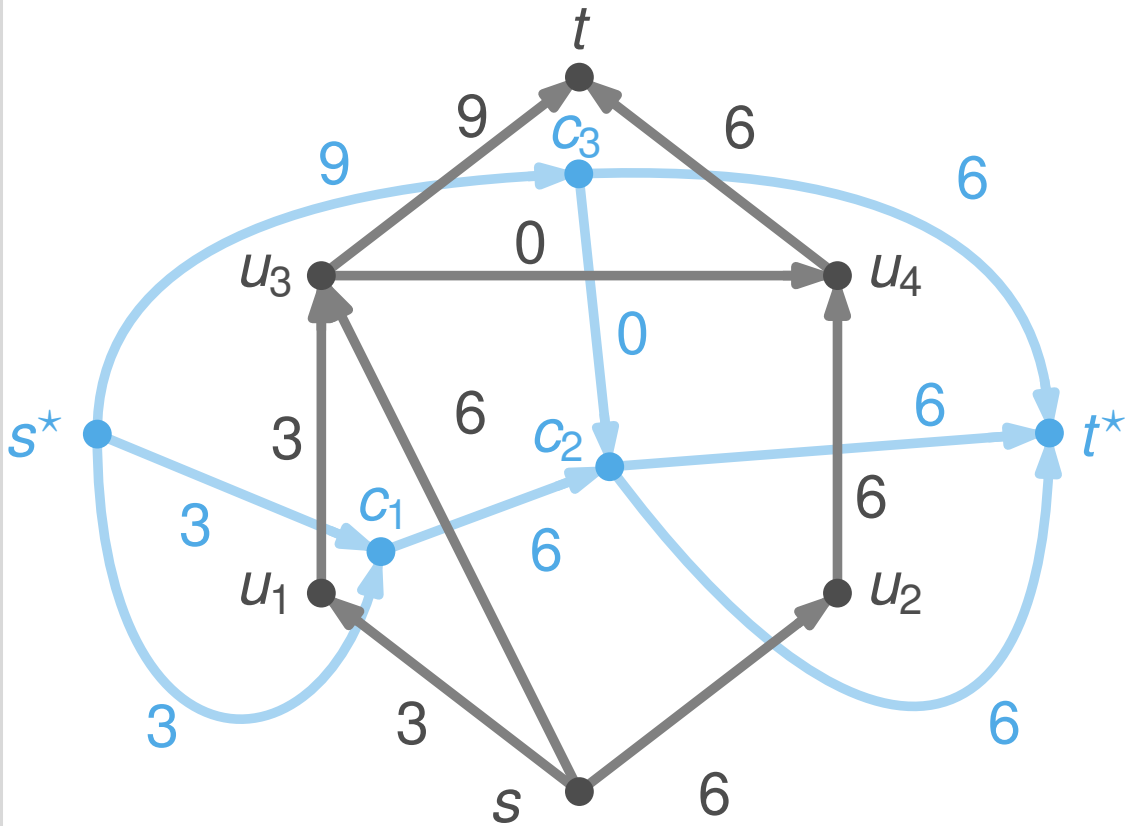
	17	13	
17		13	
		44	9
7	7	14	9
	14		9
7	7		9
			30

# Wrong Conflict Resolution



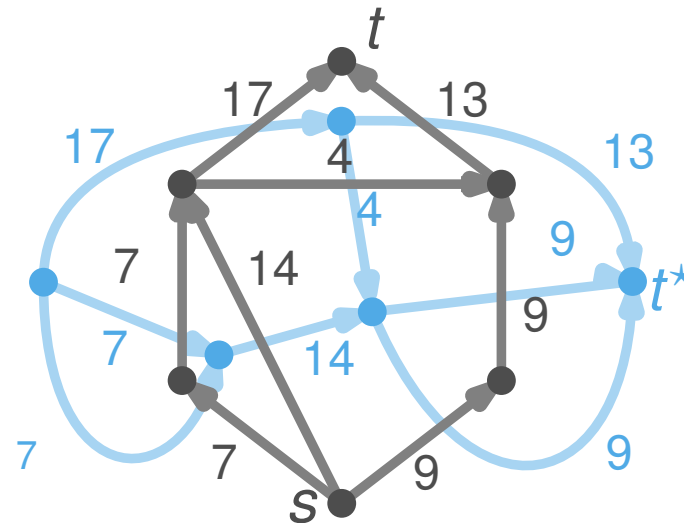
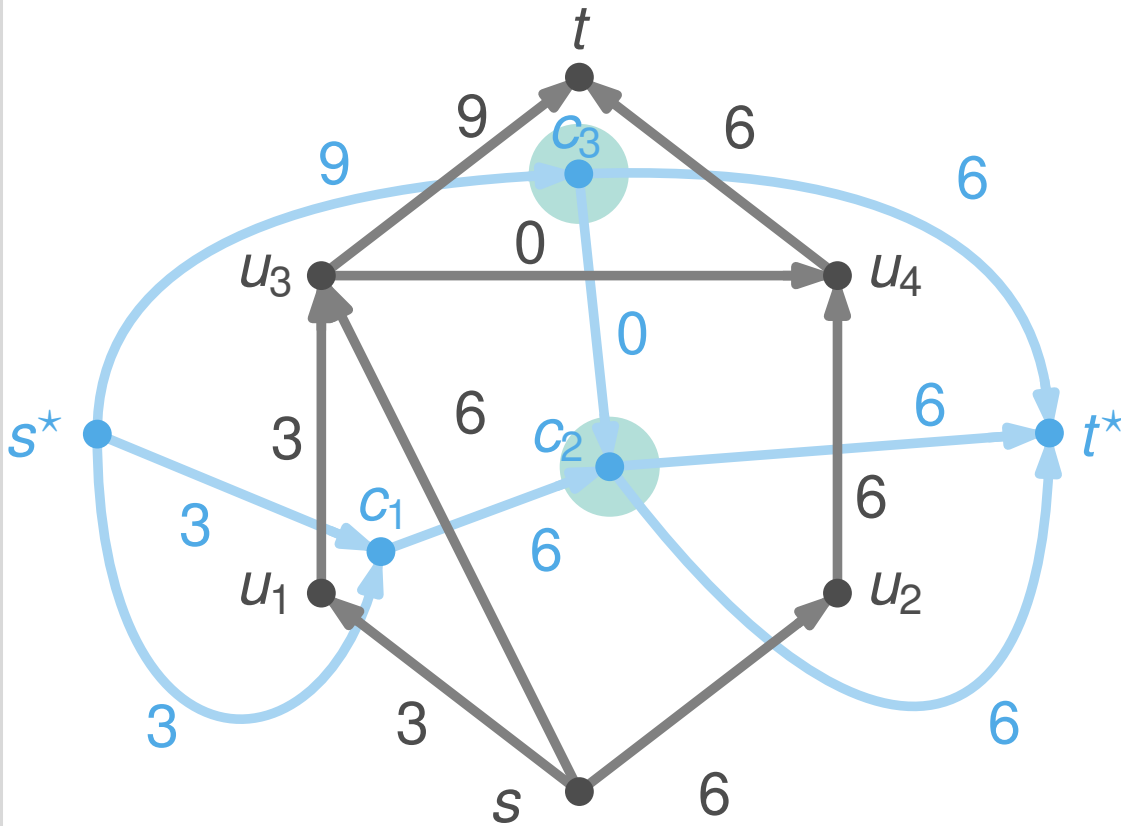
	17	13	
17		13	
		44	9
7	7	14	9
	14		9
7	7		9
			30

# Wrong Conflict Resolution



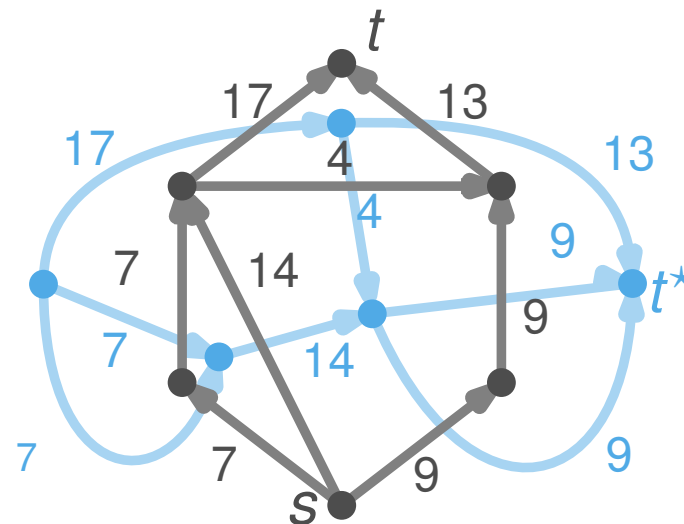
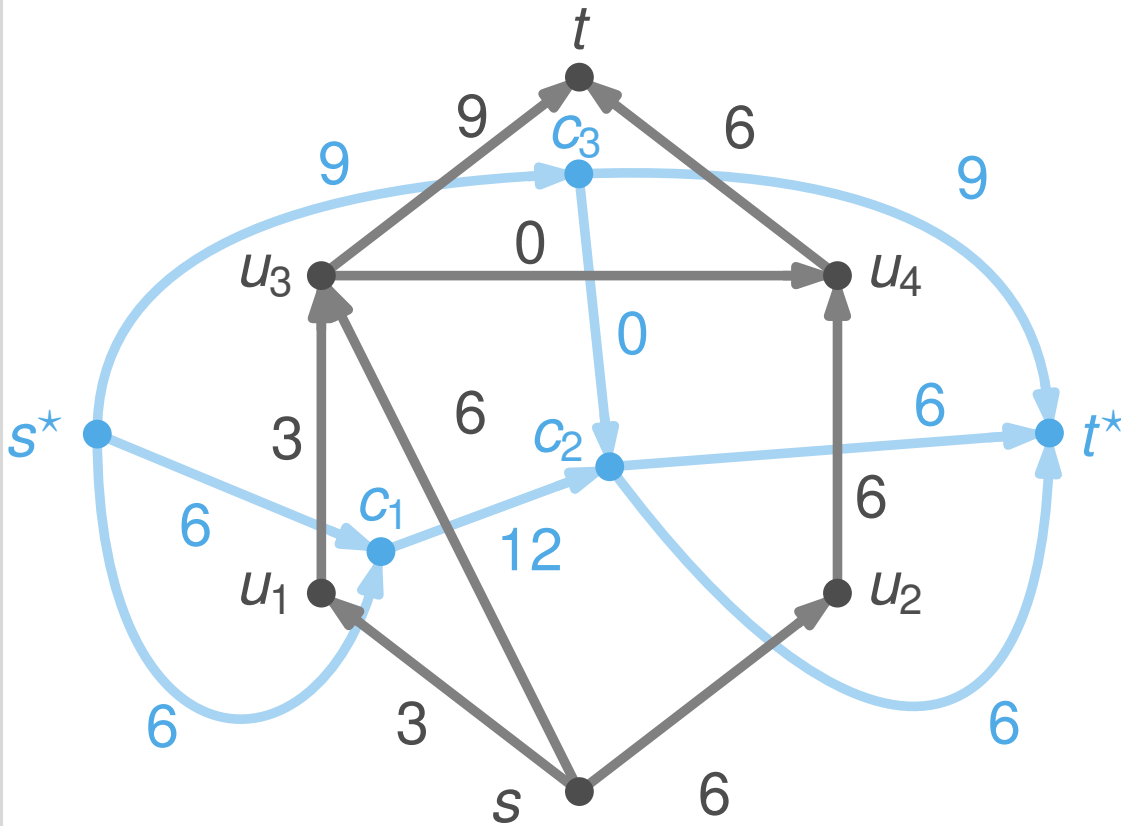
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17		13	
		44	9
7	7	14	9
	14		9
7	7		9
			30

# Wrong Conflict Resolution



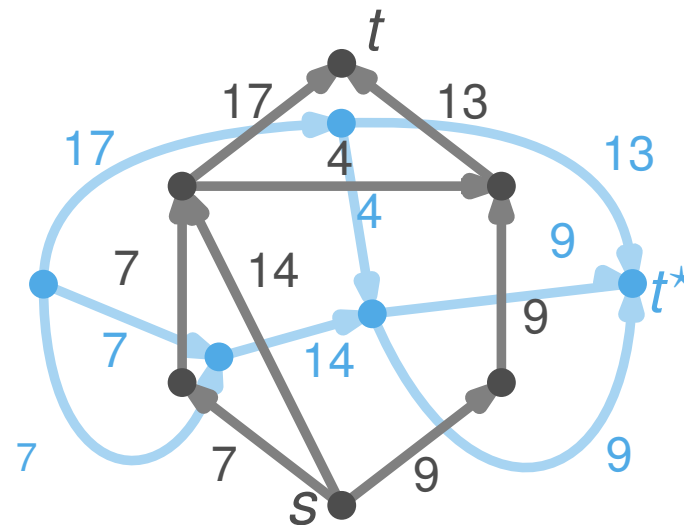
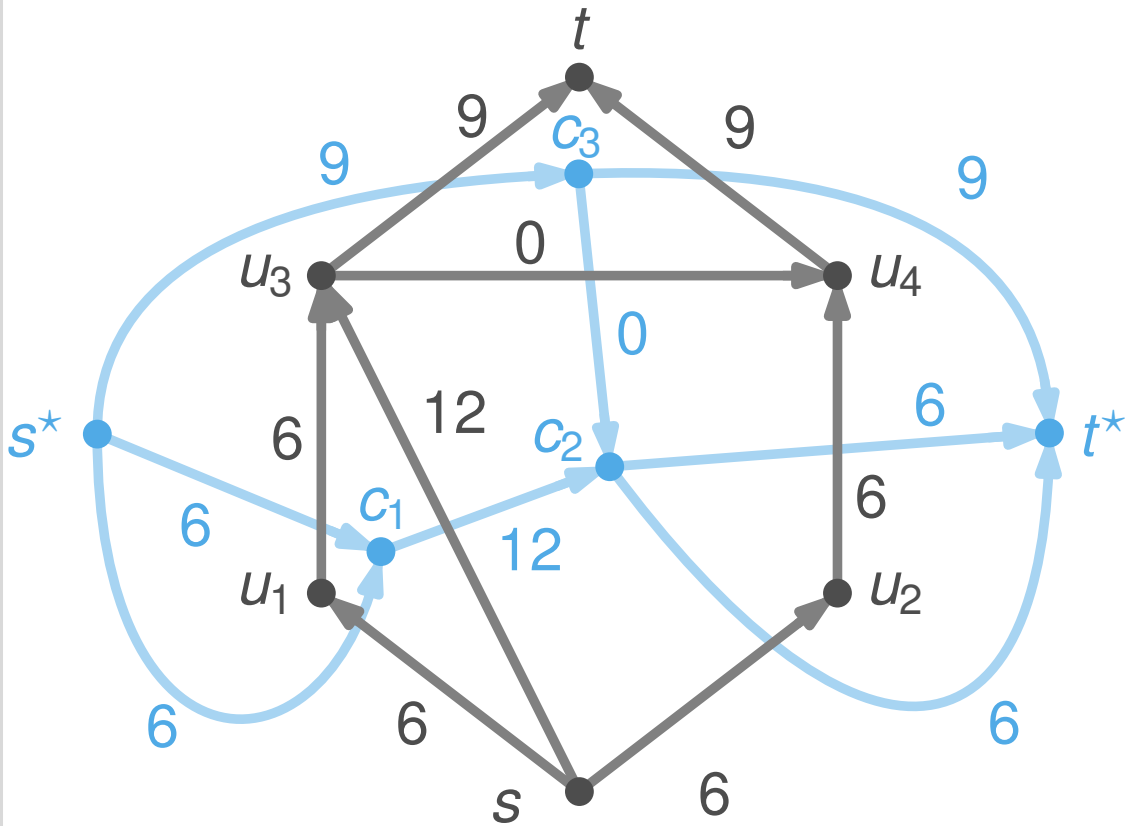
	17	13	
17		13	
		44	9
7	7	14	9
			9
7	7	14	9
			9
			30

# Wrong Conflict Resolution



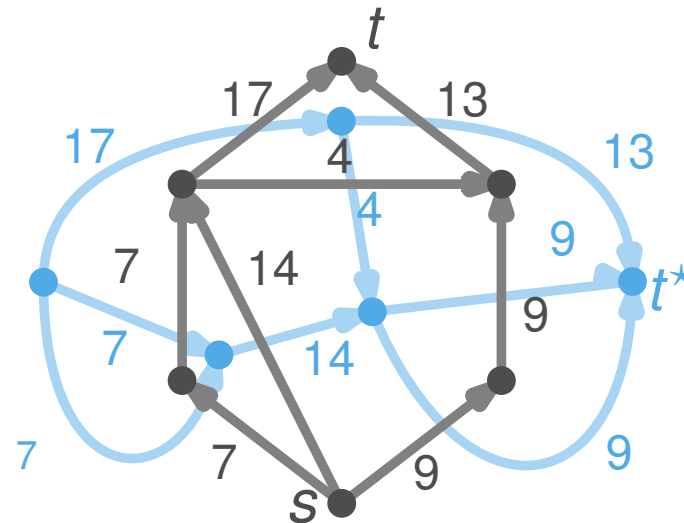
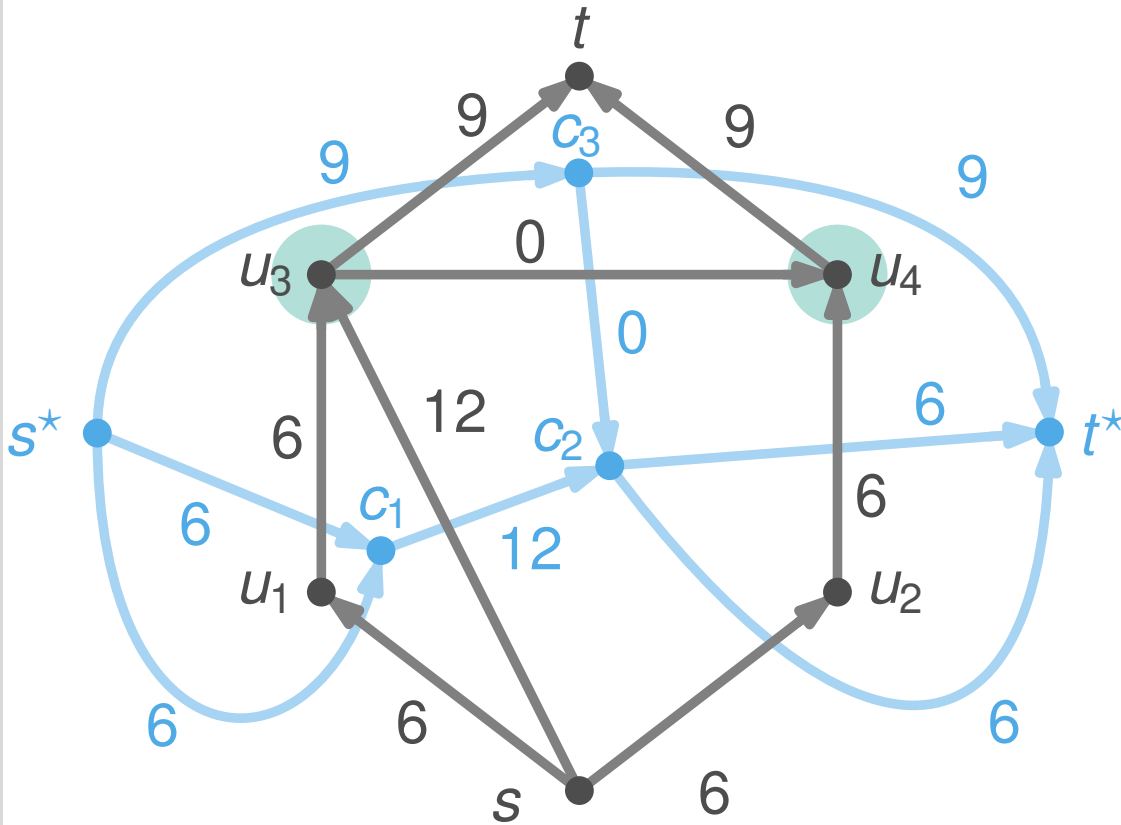
	17	13	
17		13	
		44	9
7	7	14	9
			9
7	7		9
			30

# Wrong Conflict Resolution



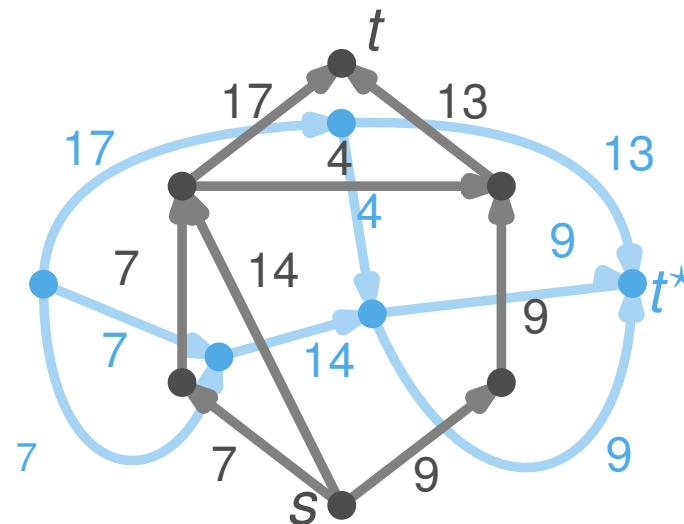
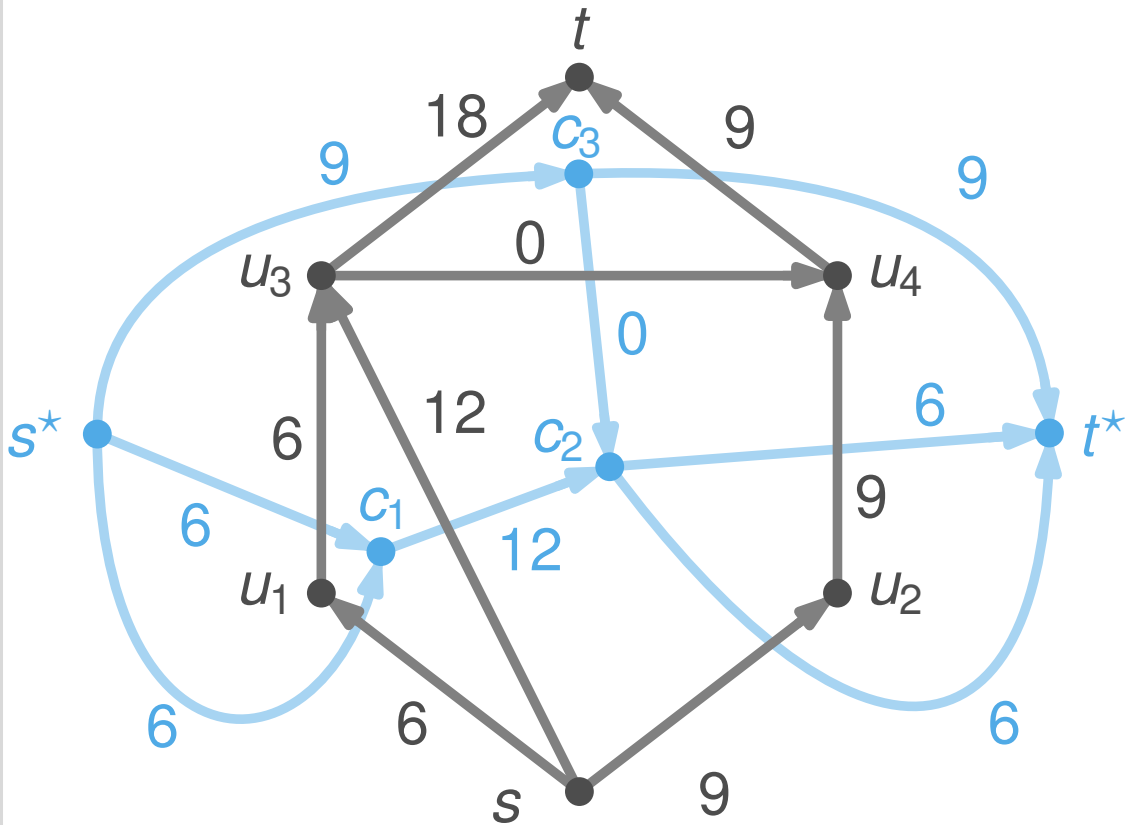
	17	13	
17		13	
		44	9
7	7	14	9
			9
7	7	14	9
			9
			30

# Wrong Conflict Resolution



	17	13	
17		13	
		44	9
7	7	14	9
	14		9
7	7		9
			30

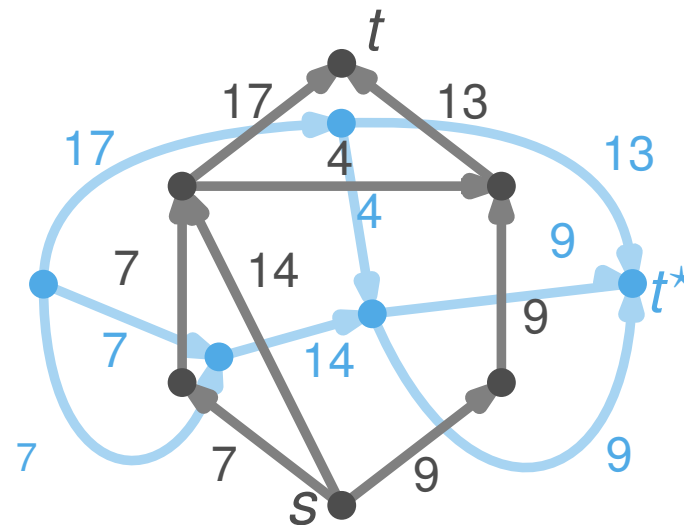
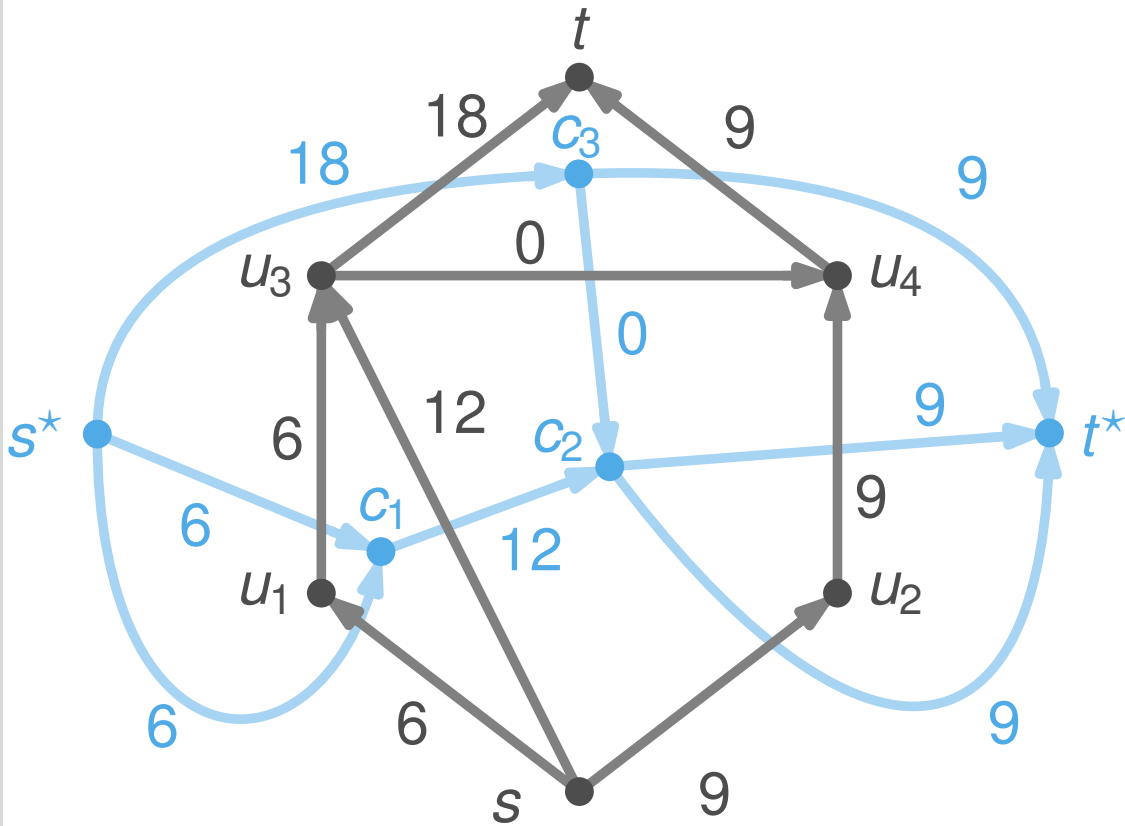
# Wrong Conflict Resolution



	17	13	
17		13	
		44	9
7	7	14	9
			9
7	7	14	9
			9
			30

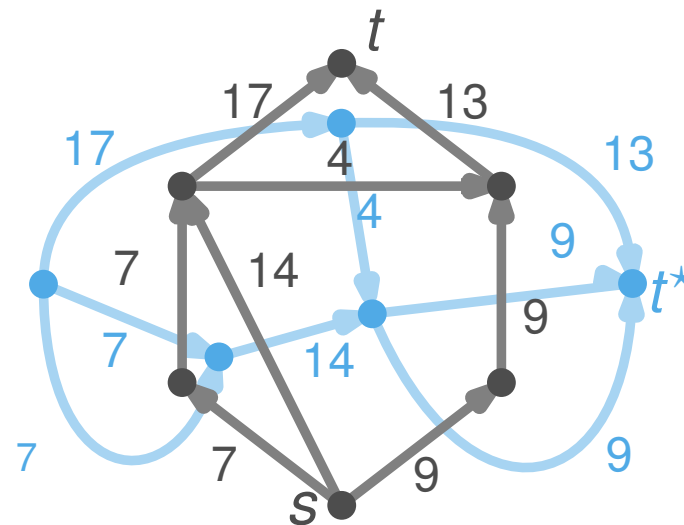
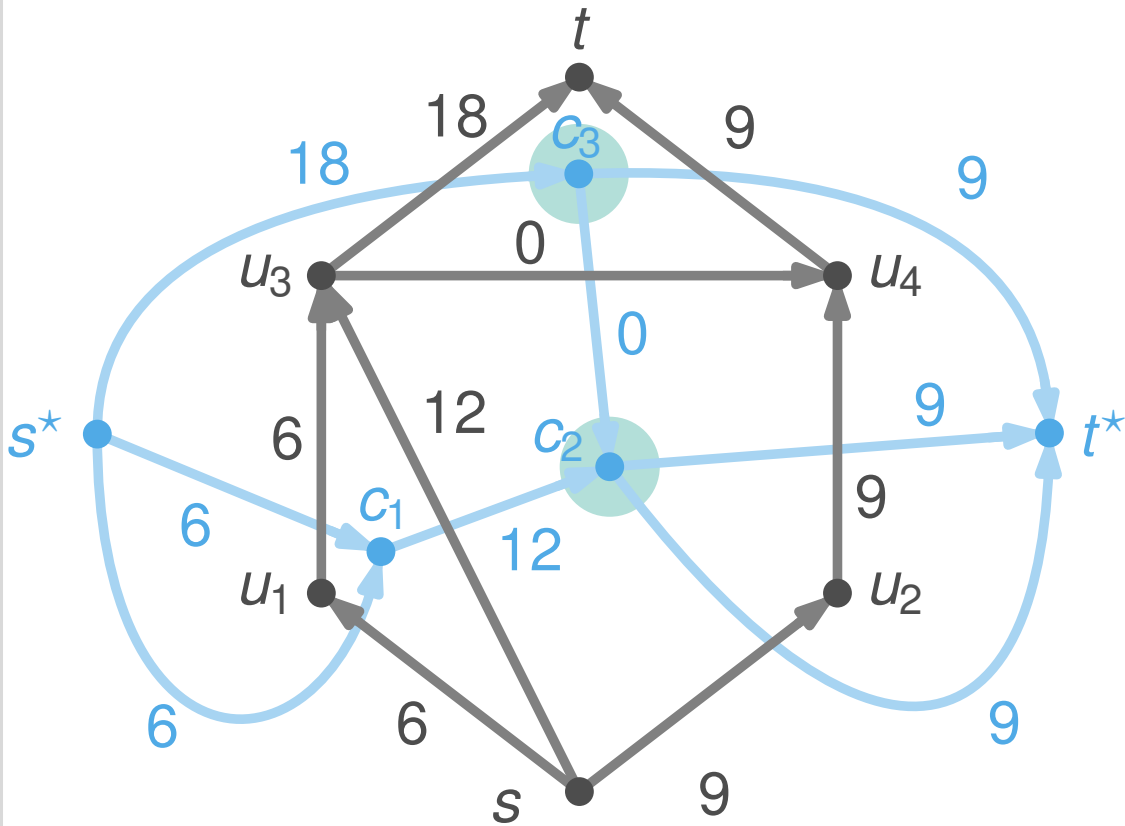


# Wrong Conflict Resolution



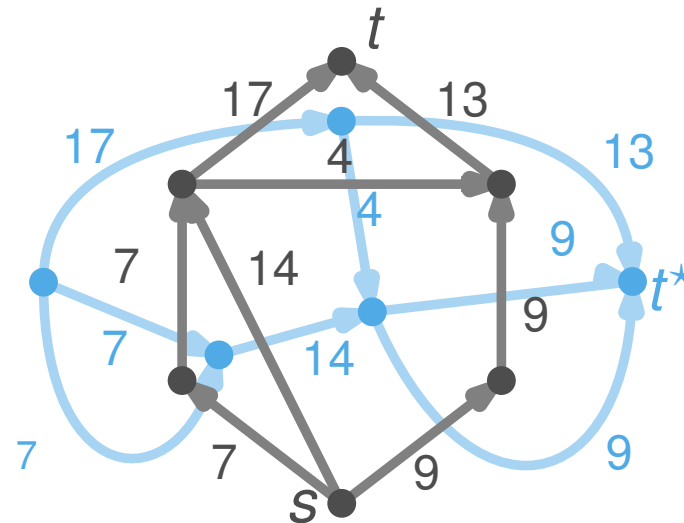
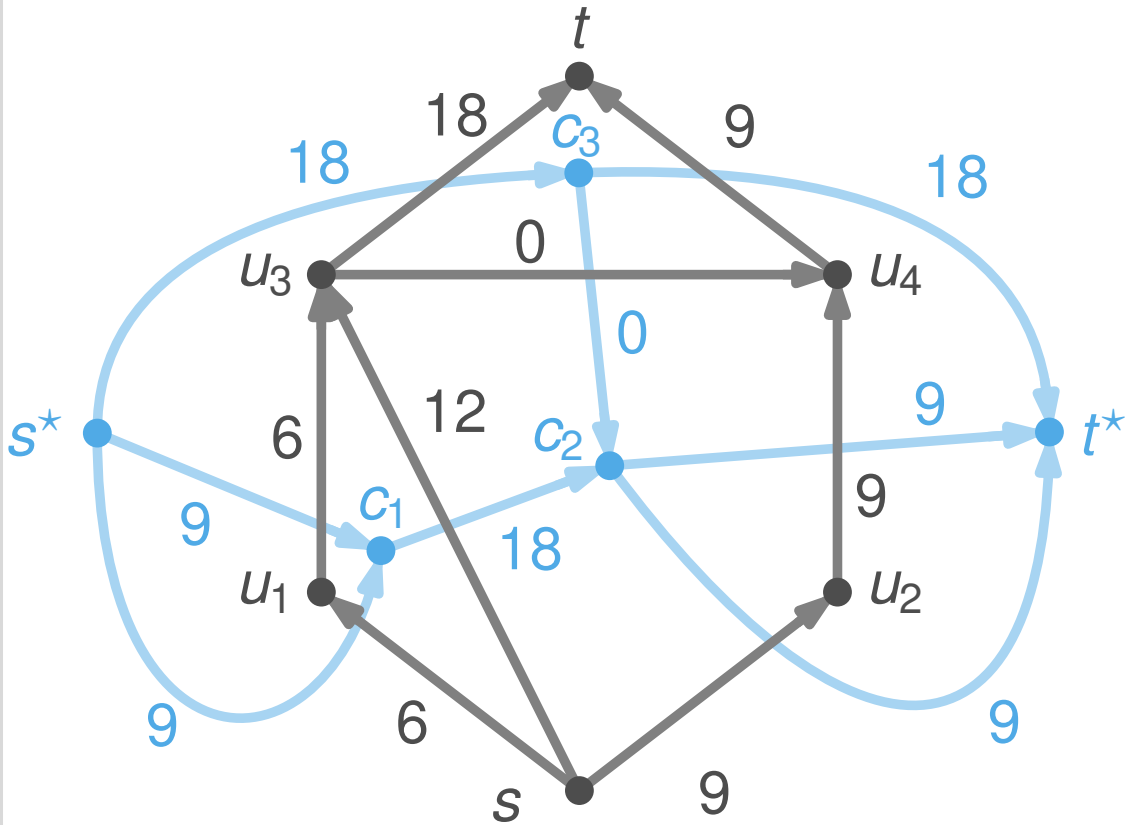
	17	13	
17		13	
		44	9
7	7	14	9
7	7	14	9
			30

# Wrong Conflict Resolution



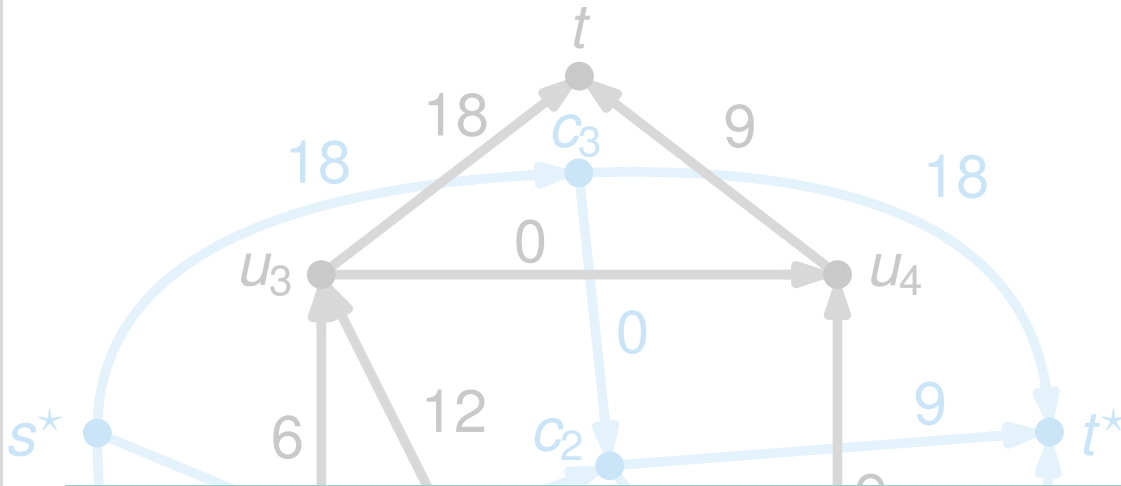
	17	13	
17		13	
		44	9
7	7	14	9
			9
7	7	14	9
			9
			30

# Wrong Conflict Resolution



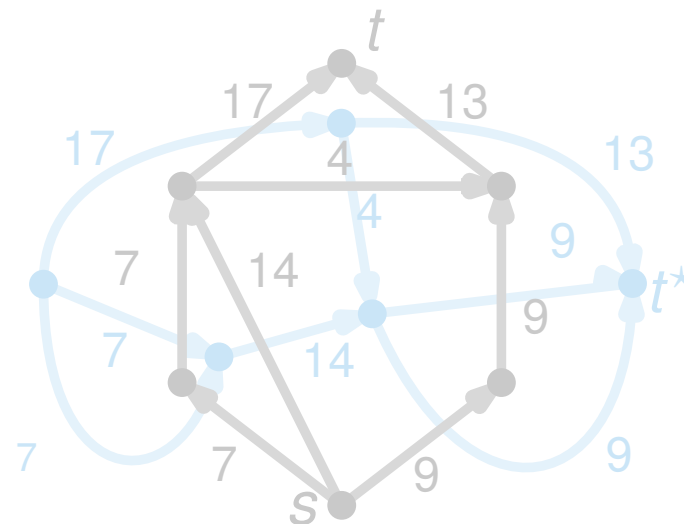
	17	13	
17		13	
		44	9
7	7	14	9
	14		9
7	7		9
			30

# Wrong Conflict Resolution



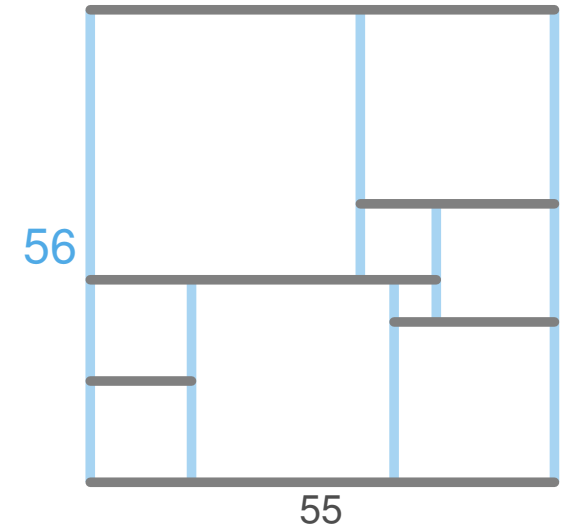
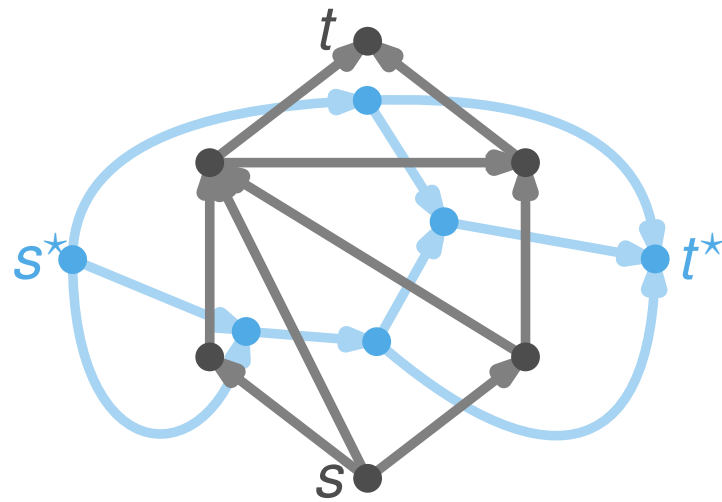
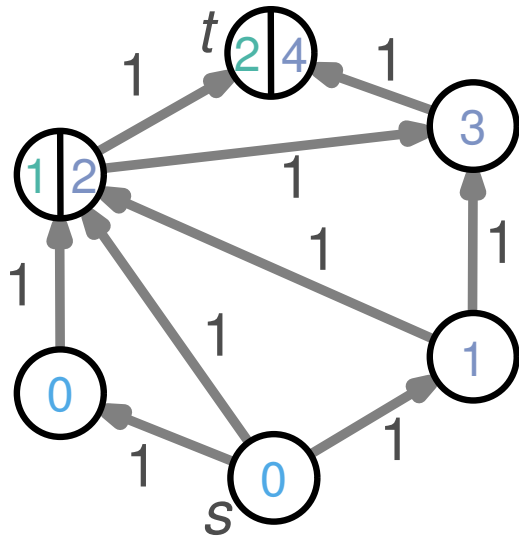
## Observation 6

A wrong conflict resolution might never lead to a feasible power flow.

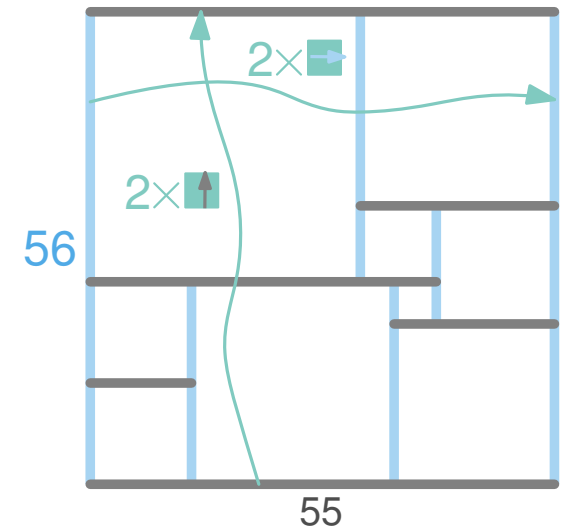
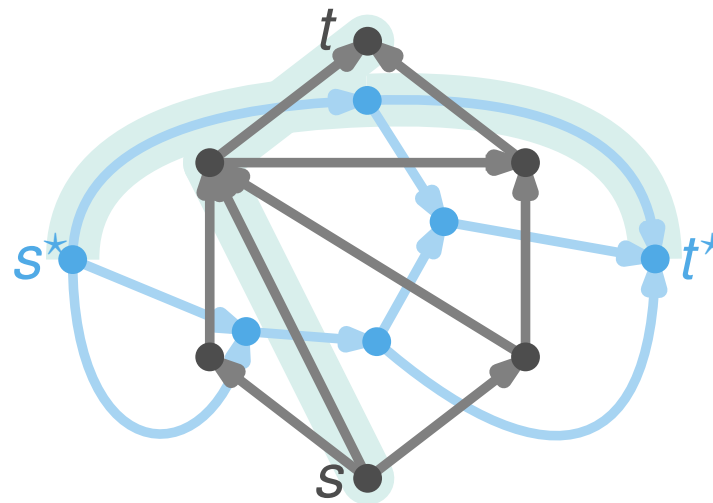
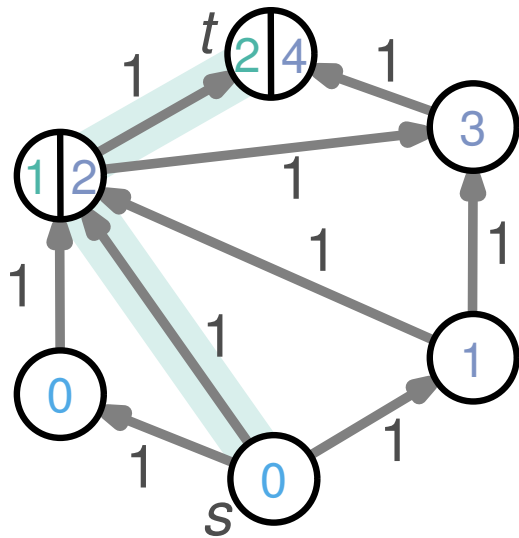


	17	13	
17		13	
7	7	14	9
7	7	14	9
			31
			30

# The Property of Balancing

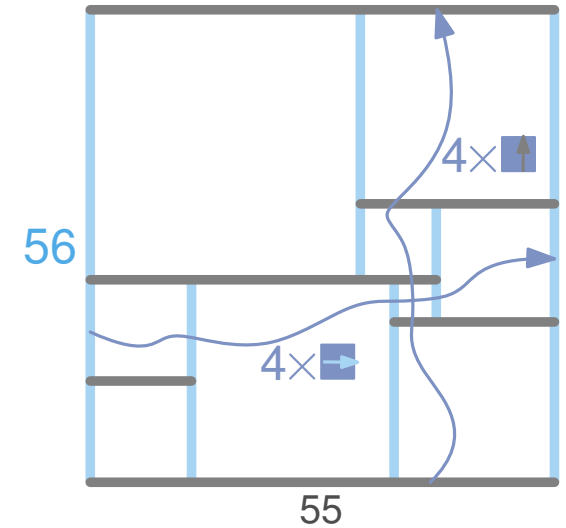
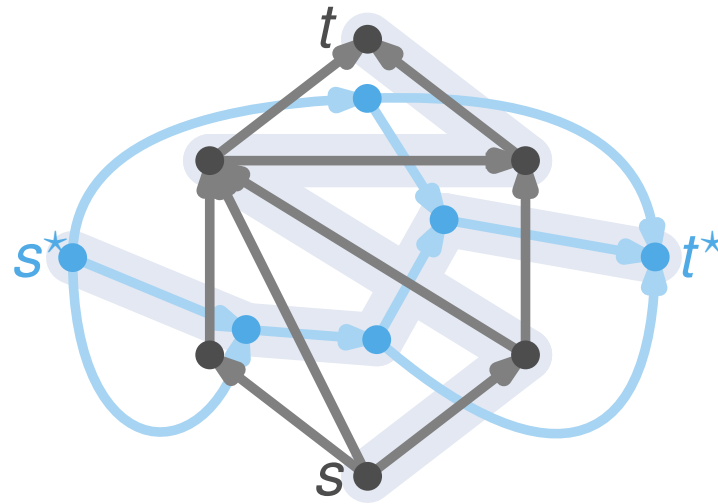
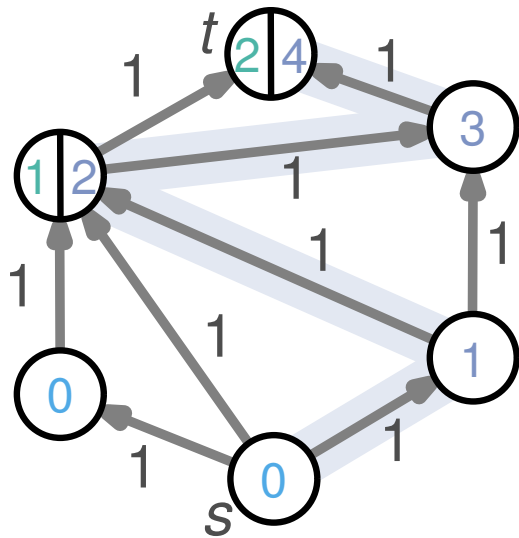


# The Property of Balancing



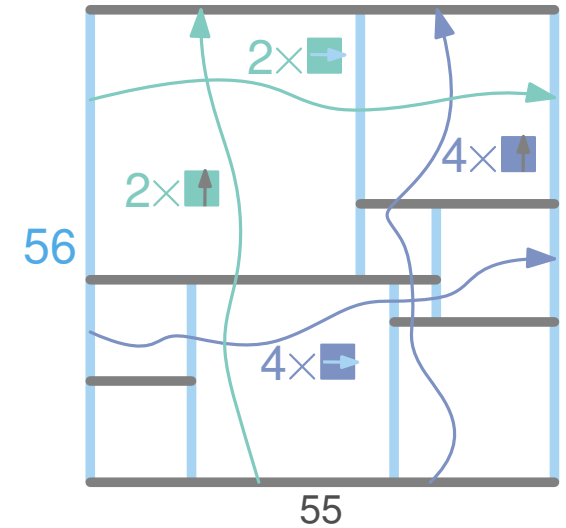
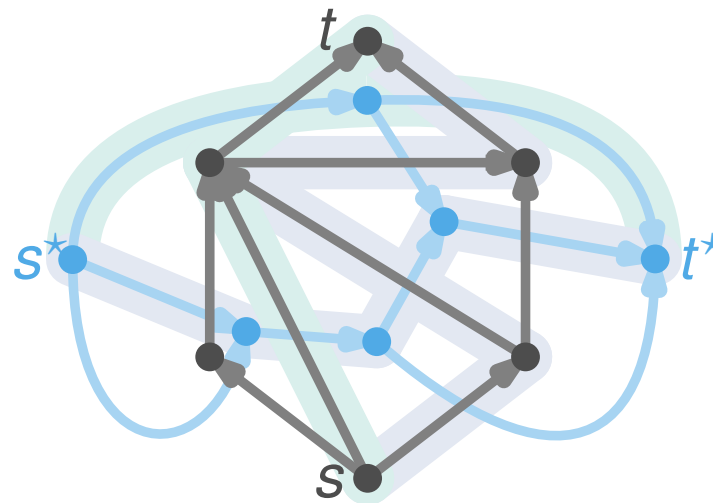
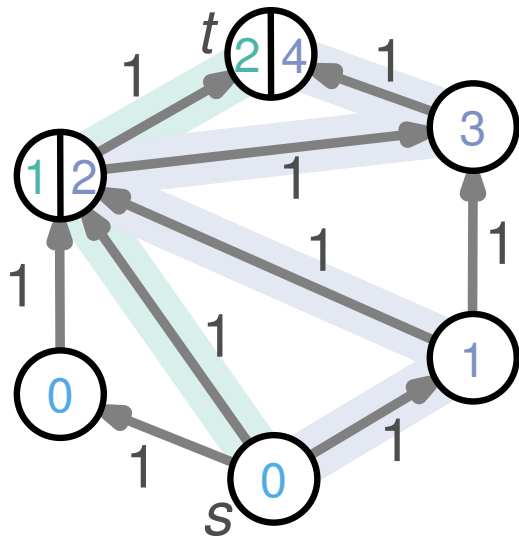
 shortest path



# The Property of Balancing



 longest path

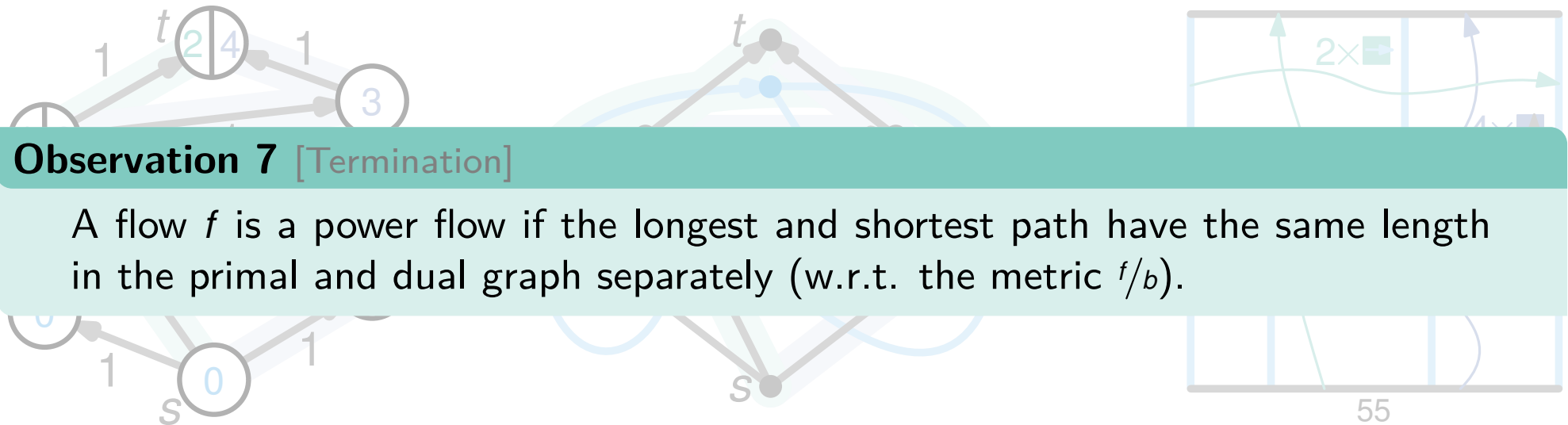
# The Property of Balancing



-  shortest path
-  longest path

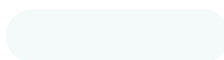



# The Property of Balancing



## Observation 7 [Termination]

A flow  $f$  is a power flow if the longest and shortest path have the same length in the primal and dual graph separately (w.r.t. the metric  $f/b$ ).

-  shortest path
-  longest path

- Graph-theoretical flow algorithms use scaling techniques
  1. Capacity scaling [Edmonds and Karp, 1972]
  2. Excess scaling [Ahuja and Orlin, 1989]
- Power flows excluding a trivial power flow ( $f \equiv 0$ ) can be scaled up and down by a factor  $\chi$

## Lemma 8 [Scaling]

Every non-zero electrical flow  $f' : E \rightarrow \mathbb{R}_{>0}$  can be rescaled to a new feasible electrical flow  $f$  by applying a scaling factor

$$0 \leq \chi \leq \min_{e' \in E} \frac{\text{cap}(e')}{f'(e')} =: \bar{\chi} \quad (1)$$

to  $f(e) = f'(e) \cdot \chi$  for all  $e \in E$ .

# Continuous Changes to the Power Grid

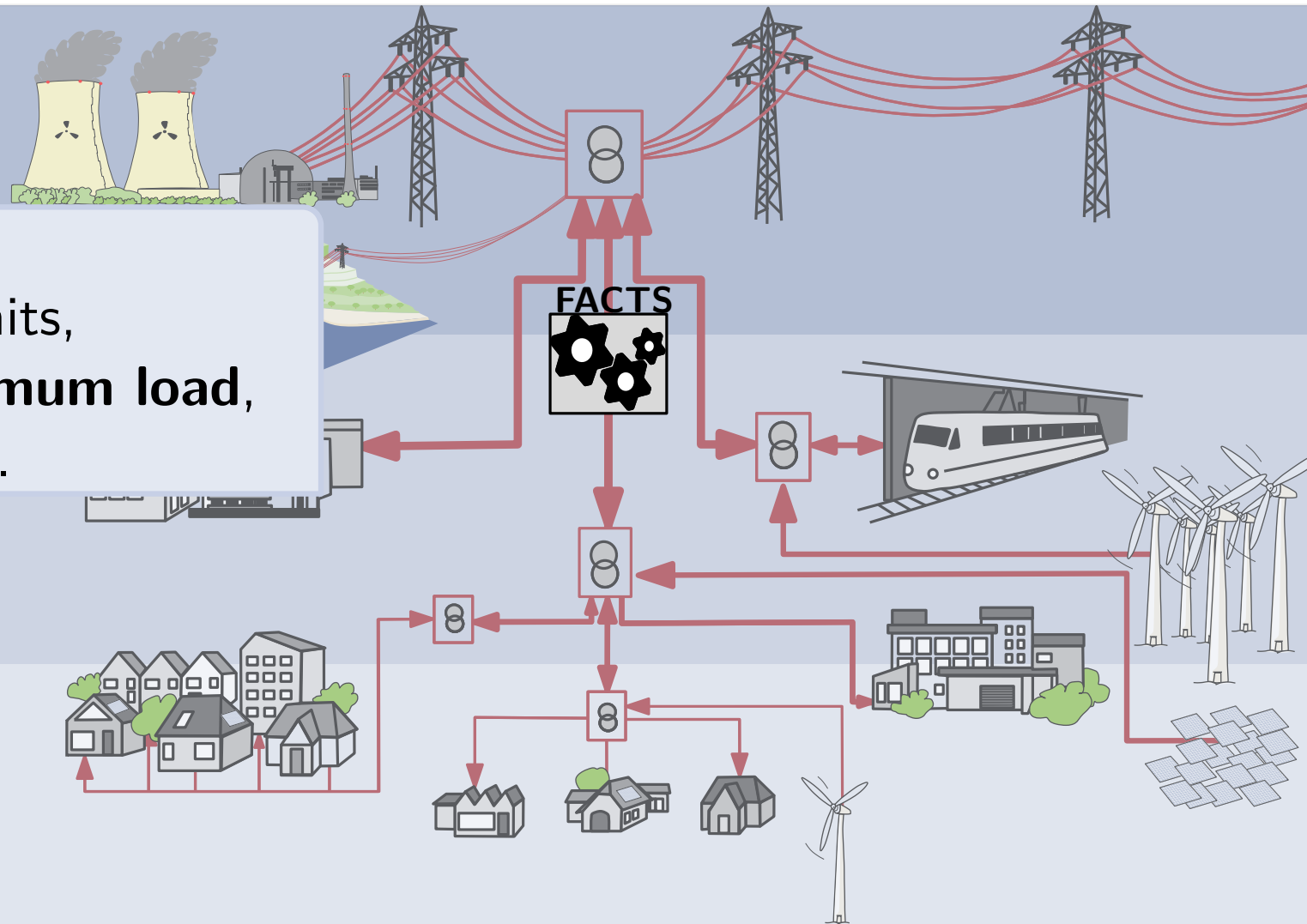
Producer

FACTS...

- are **control** units,
- increase **maximum load**,
- are **expensive**.

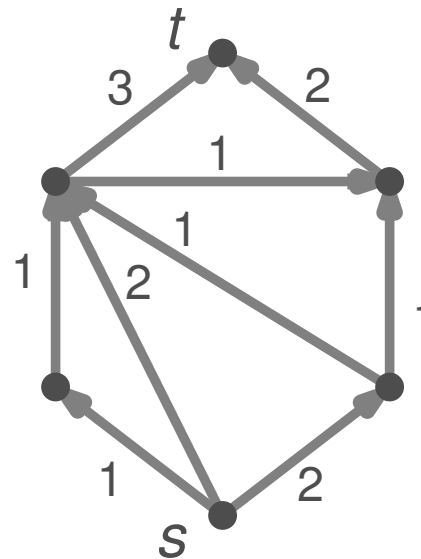
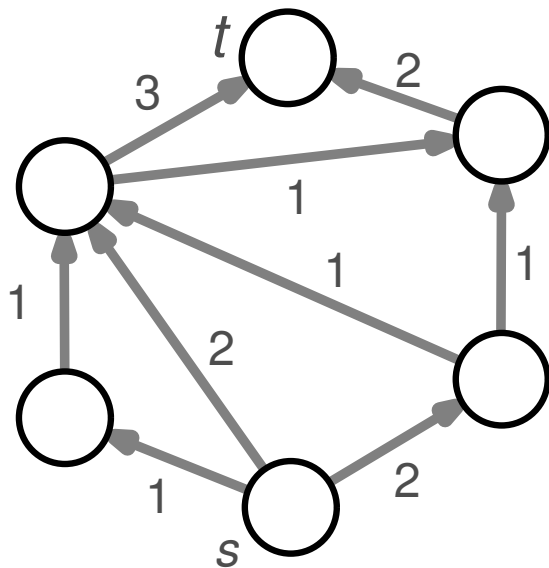
POWER GRID

Prosumer



# Susceptance Scaling

- Apply a **feasible flow**

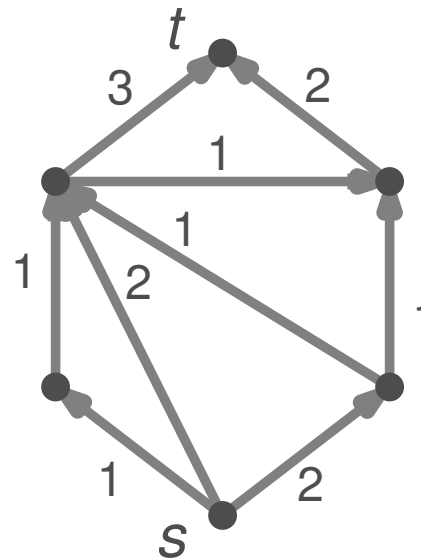
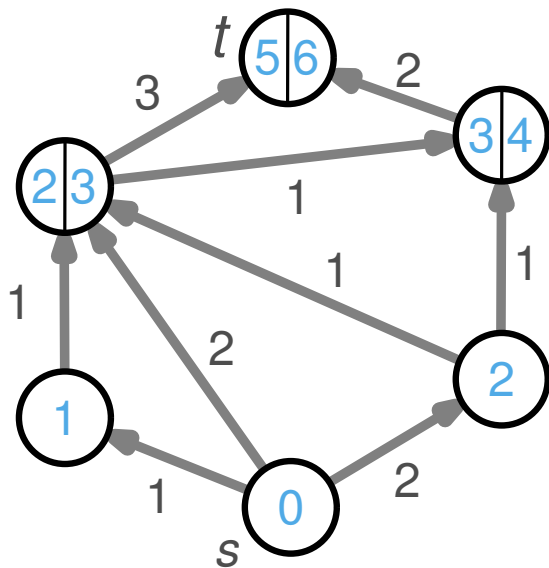


## Observation 9 [KCL and KVL Duality]

KVL conflict in the primal graph  $G$  is a KCL conflict in the dual graph  $G^*$

# Susceptance Scaling

- Apply a **feasible flow**

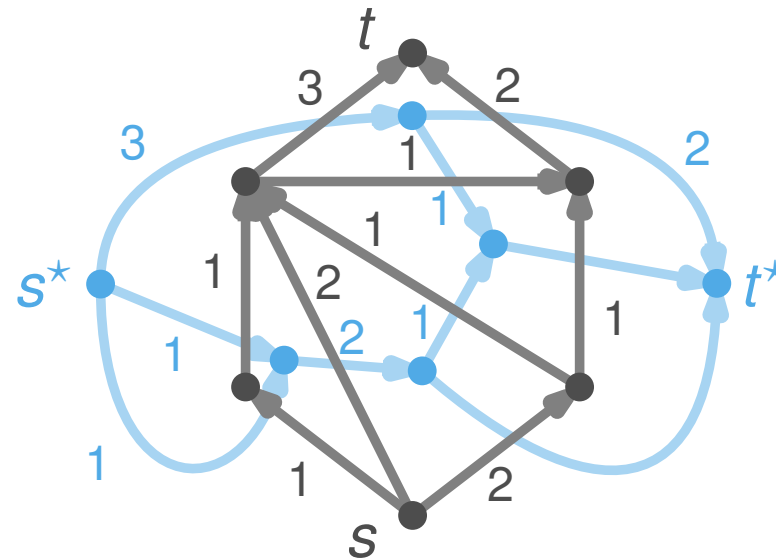
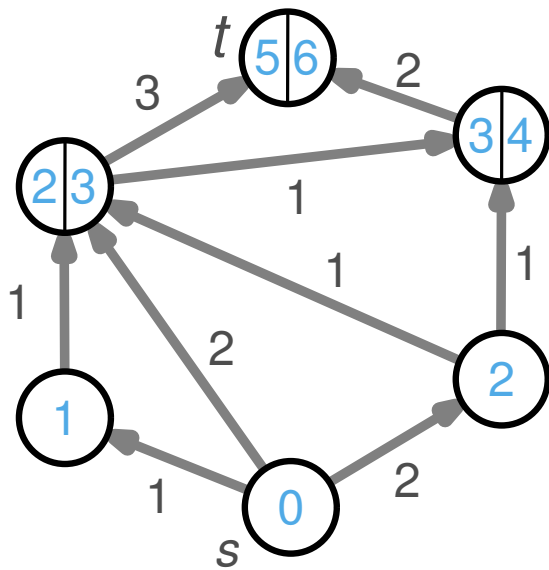


## Observation 9 [KCL and KVL Duality]

KVL conflict in the primal graph  $G$  is a KCL conflict in the dual graph  $G^*$

# Susceptance Scaling

- Apply a **feasible flow**
- Can we make it **electrical feasible**?

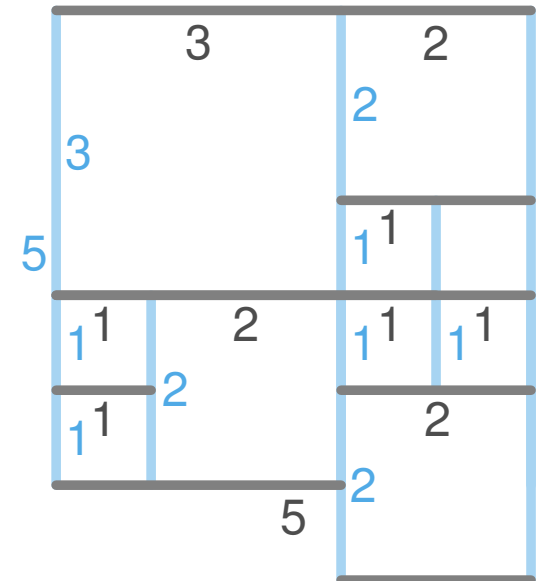
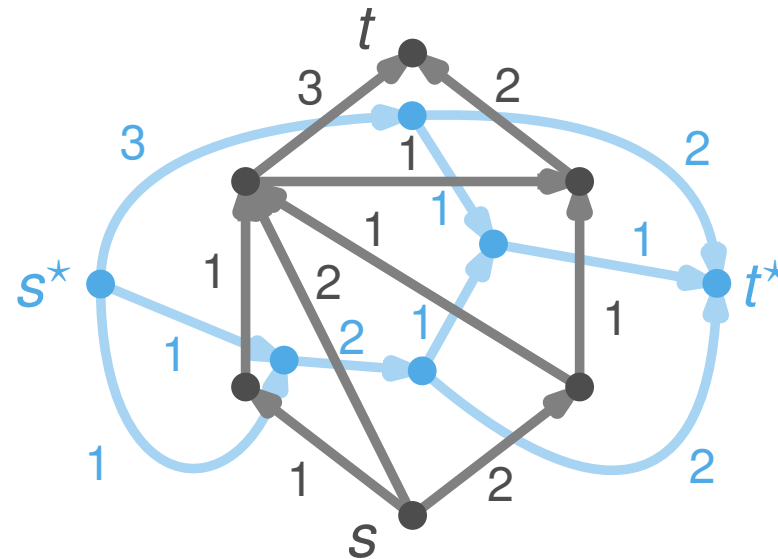
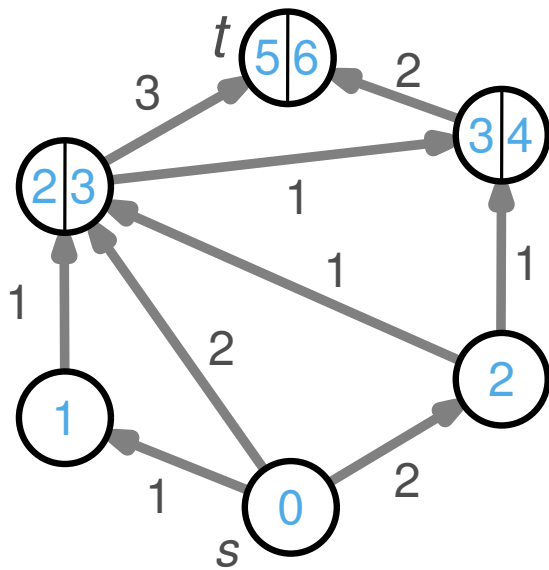


## Observation 9 [KCL and KVL Duality]

KVL conflict in the primal graph  $G$  is a KCL conflict in the dual graph  $G^*$

# Susceptance Scaling

- Apply a **feasible flow**
- Can we make it **electrical feasible**?

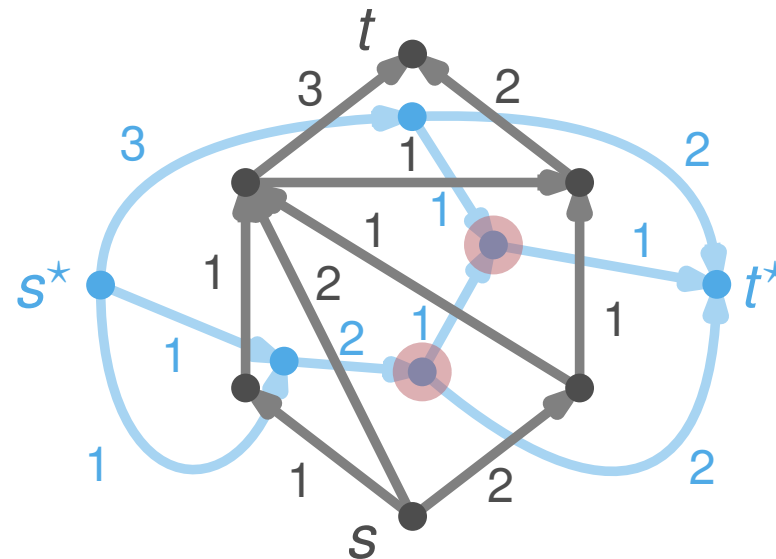
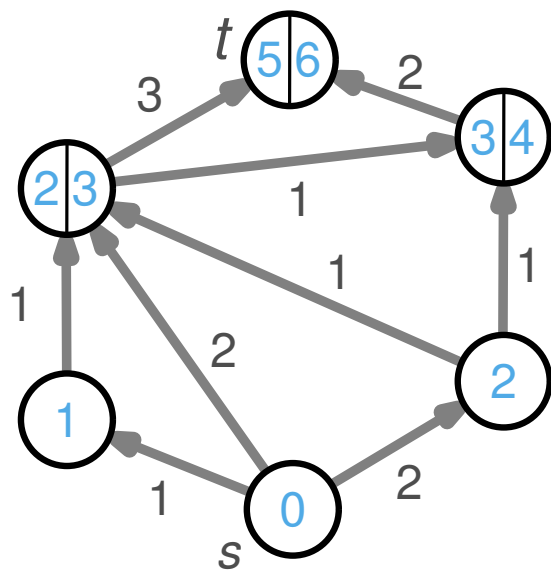


## Observation 9 [KCL and KVL Duality]

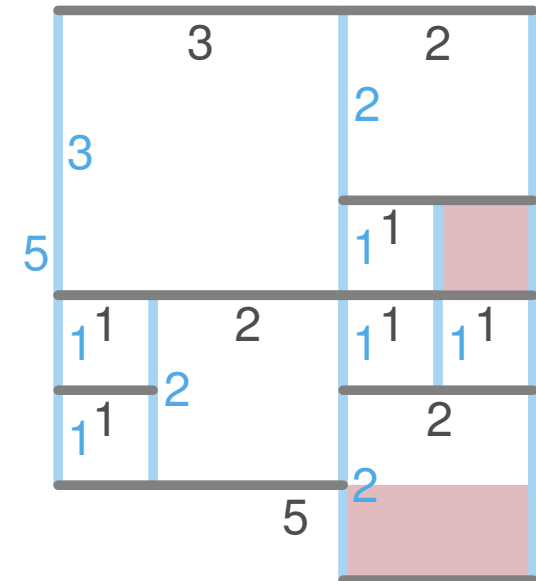
KVL conflict in the primal graph  $G$  is a KCL conflict in the dual graph  $G^*$

# Susceptance Scaling

- Apply a **feasible flow**
- Can we make it **electrical feasible**?



KCL conflict 



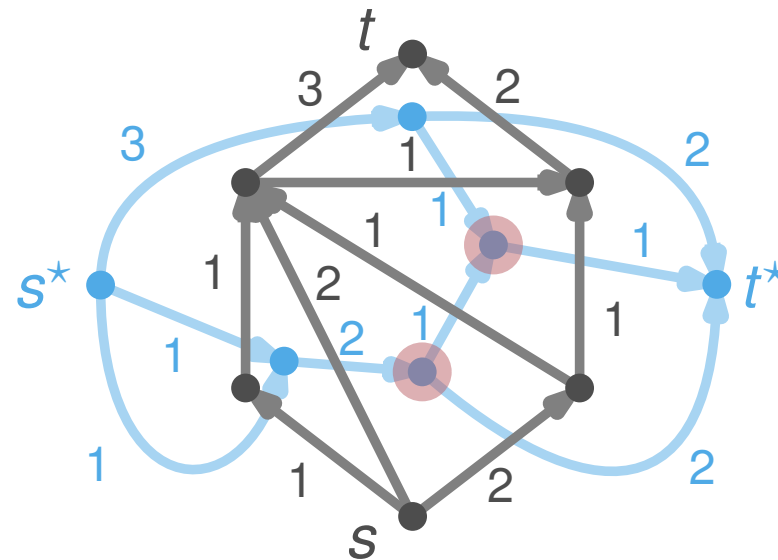
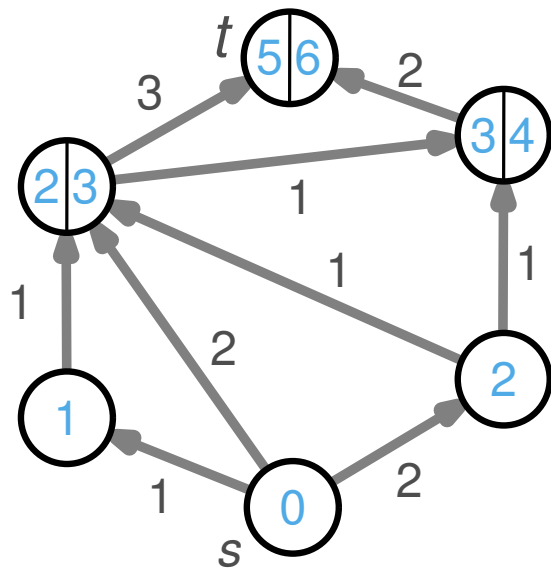
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KVL conflict in the primal graph  $G$  is a KCL conflict in the dual graph  $G^*$

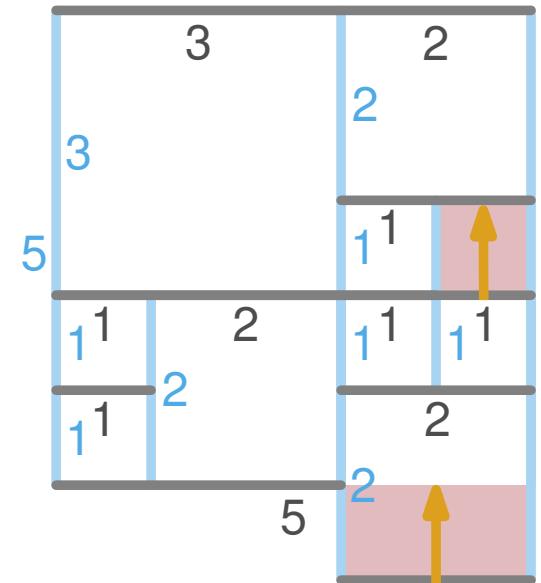


# Susceptance Scaling

- Apply a **feasible flow**
- Can we make it **electrical feasible**? ✓



KCL conflict 

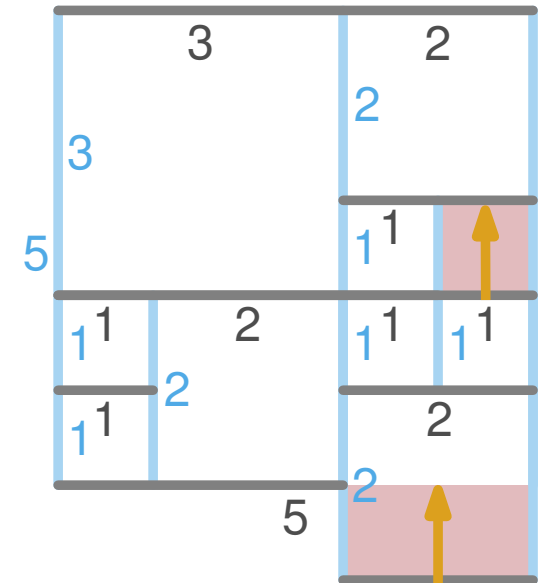
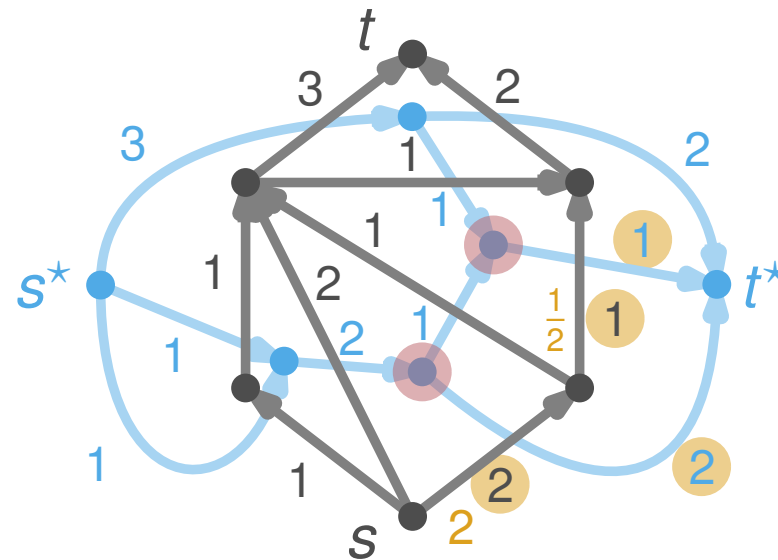
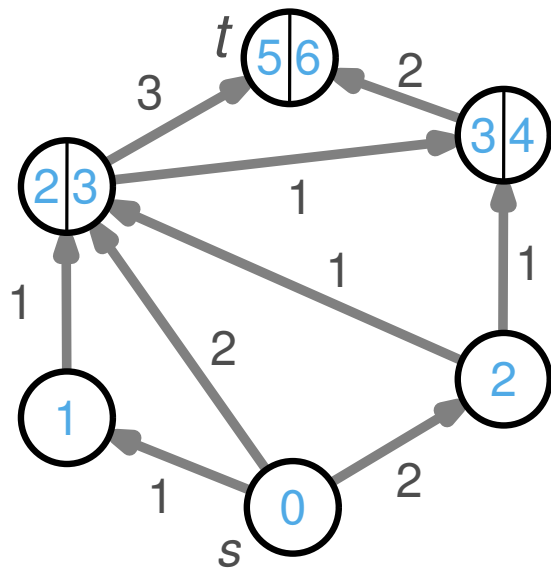


## Observation 9 [KCL and KVL Duality]

KVL conflict in the primal graph  $G$  is a KCL conflict in the dual graph  $G^*$

# Susceptance Scaling

- Apply a **feasible flow**
- Can we make it **electrical feasible**? ✓



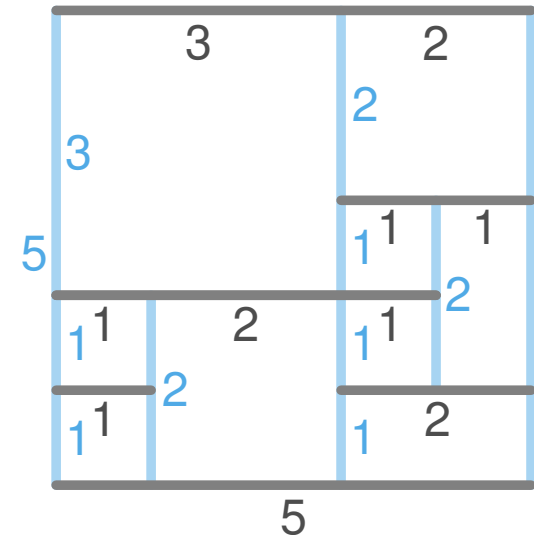
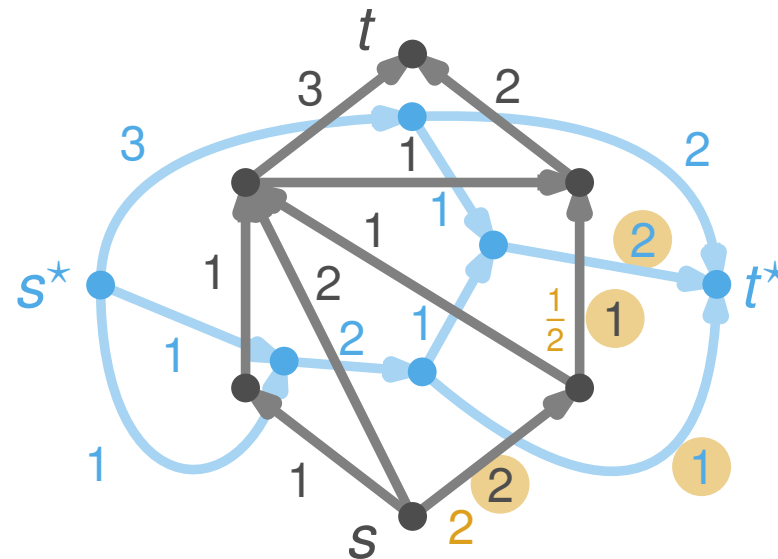
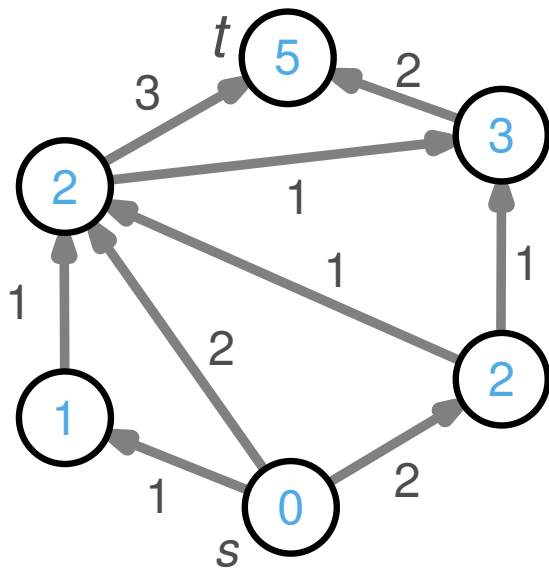
KCL conflict ●  
 b scaling ●

## Observation 9 [KCL and KVL Duality]

KVL conflict in the primal graph  $G$  is a KCL conflict in the dual graph  $G^*$

# Susceptance Scaling

- Apply a **feasible flow**
- Can we make it **electrical feasible**? ✓



$b$  scaling ●

## Observation 9 [KCL and KVL Duality]

KVL conflict in the primal graph  $G$  is a KCL conflict in the dual graph  $G^*$

# Discrete Changes to the Power Grid

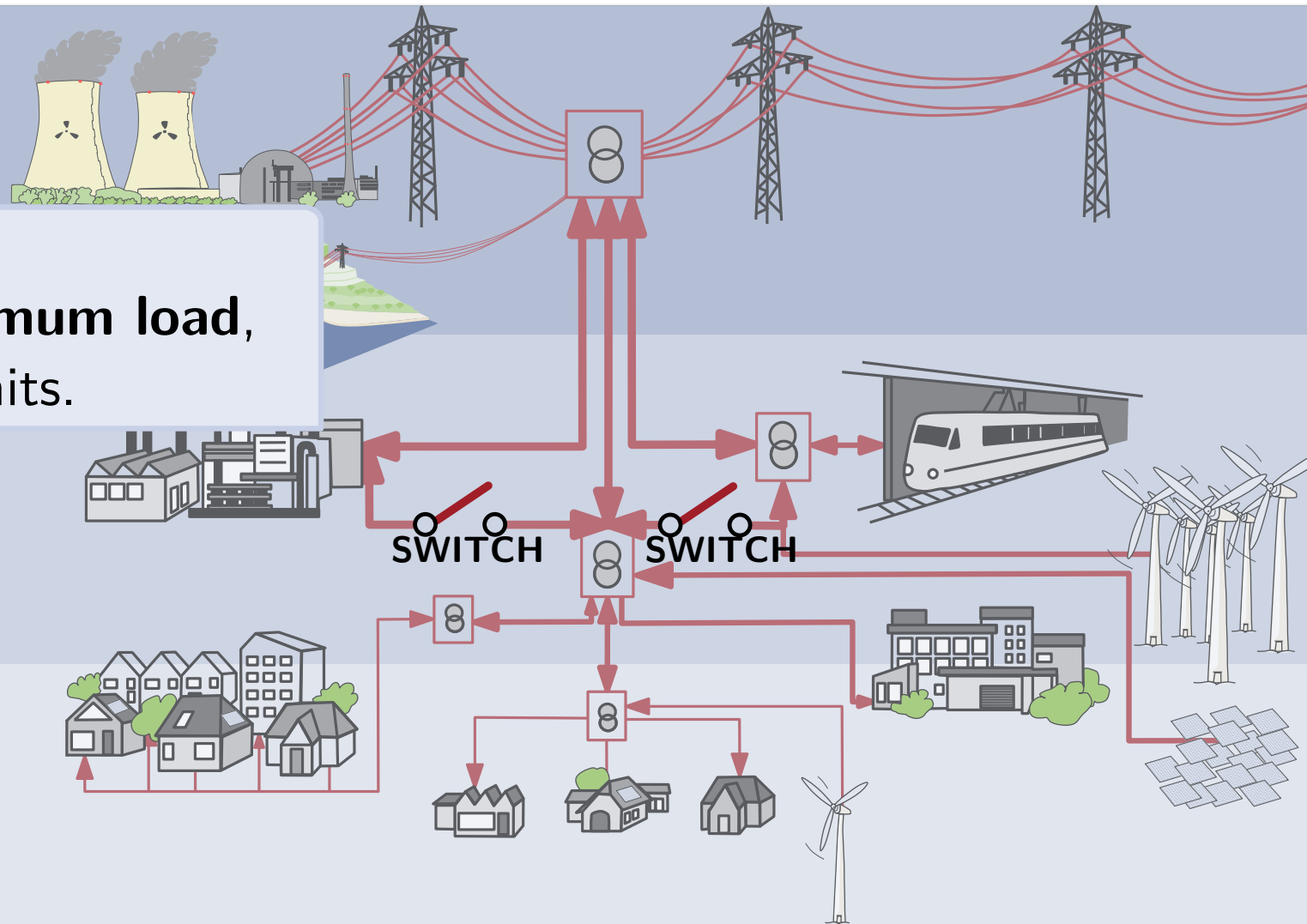
Producer

Switches...

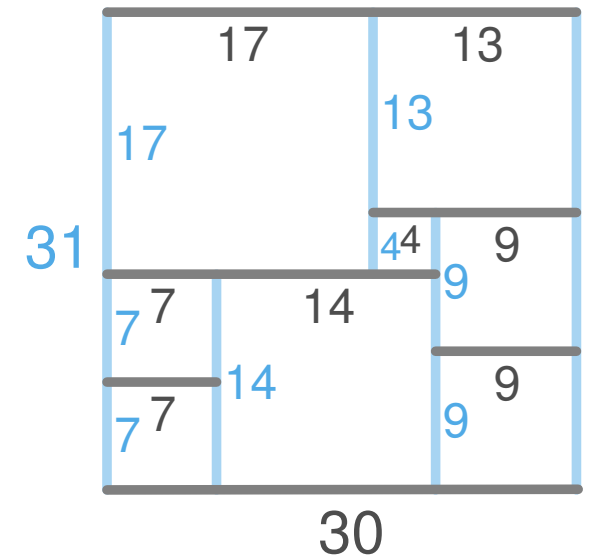
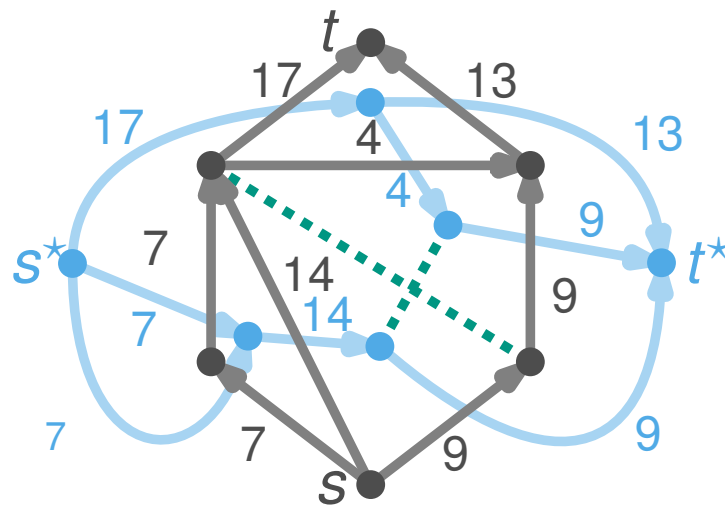
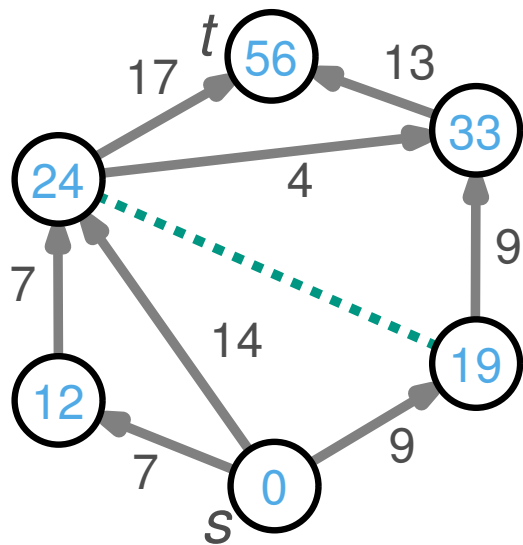
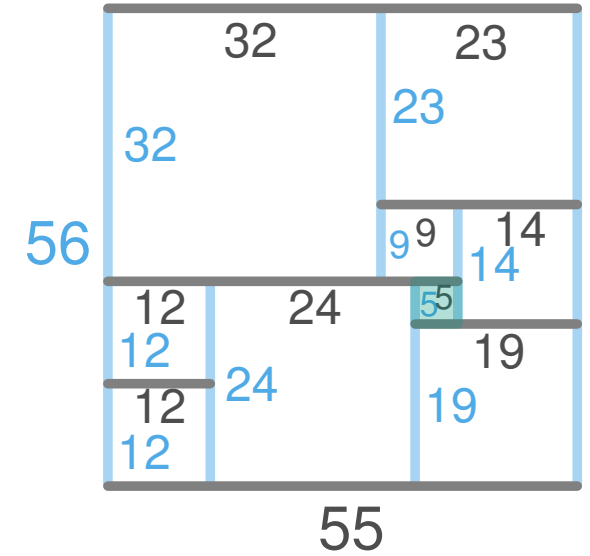
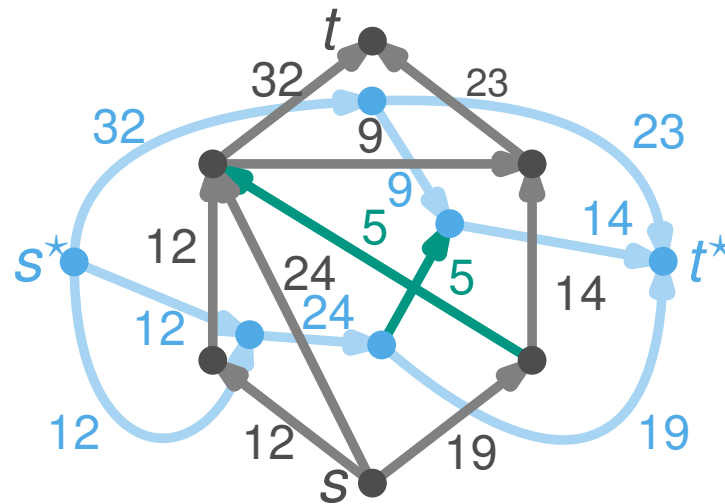
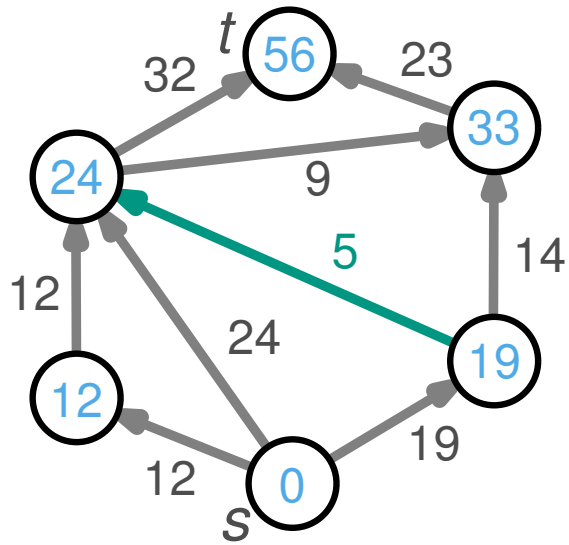
- increase **maximum load**,
- are **control** units.

Power Grid

Prosumer

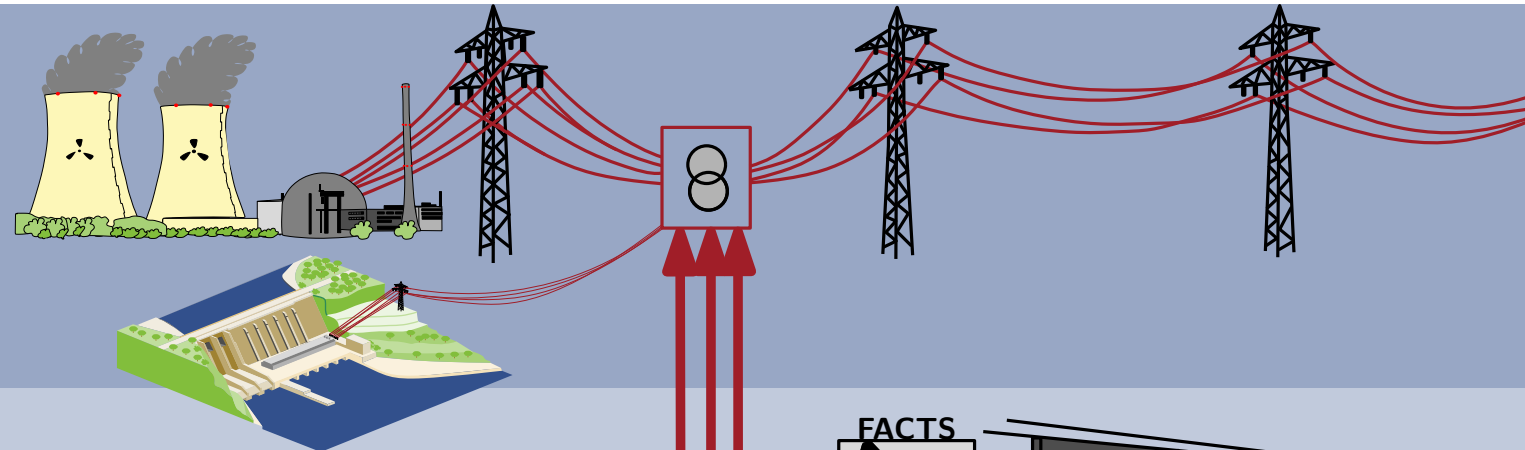


# Switching

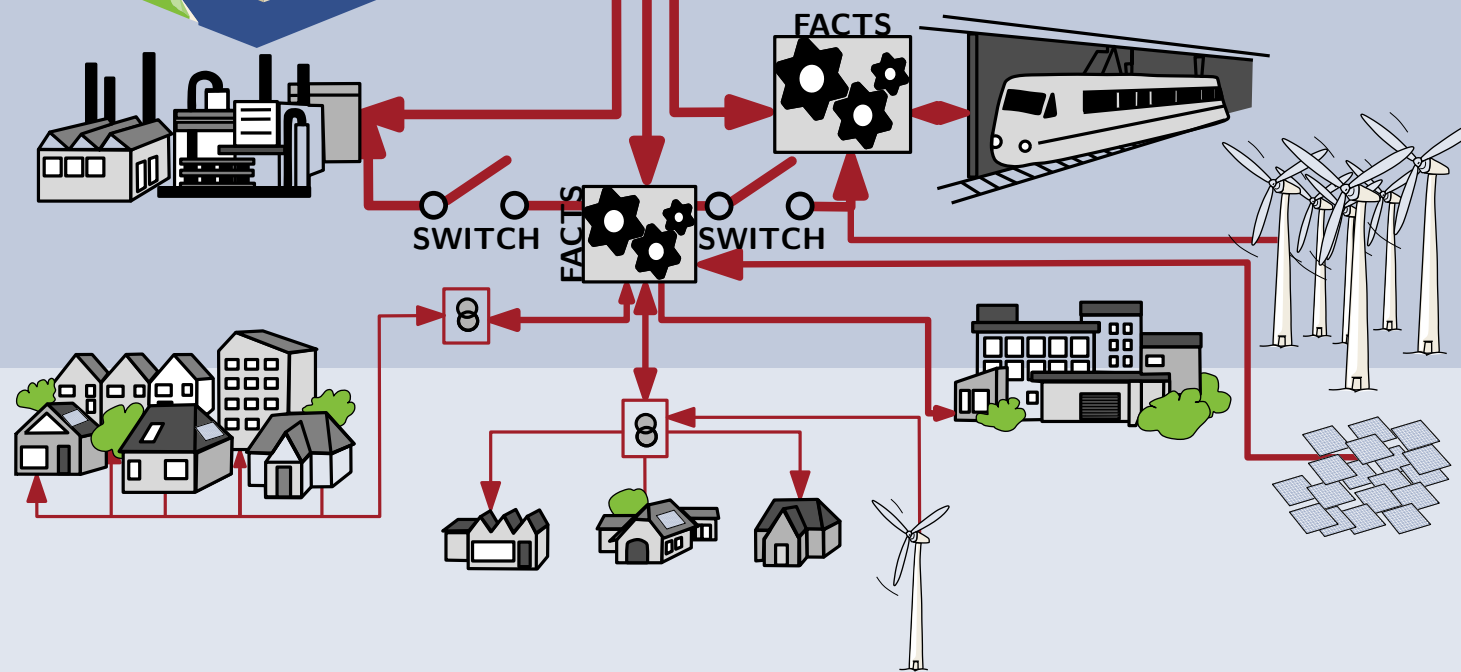


# Summary

Producer



Power Grid



Prosumer

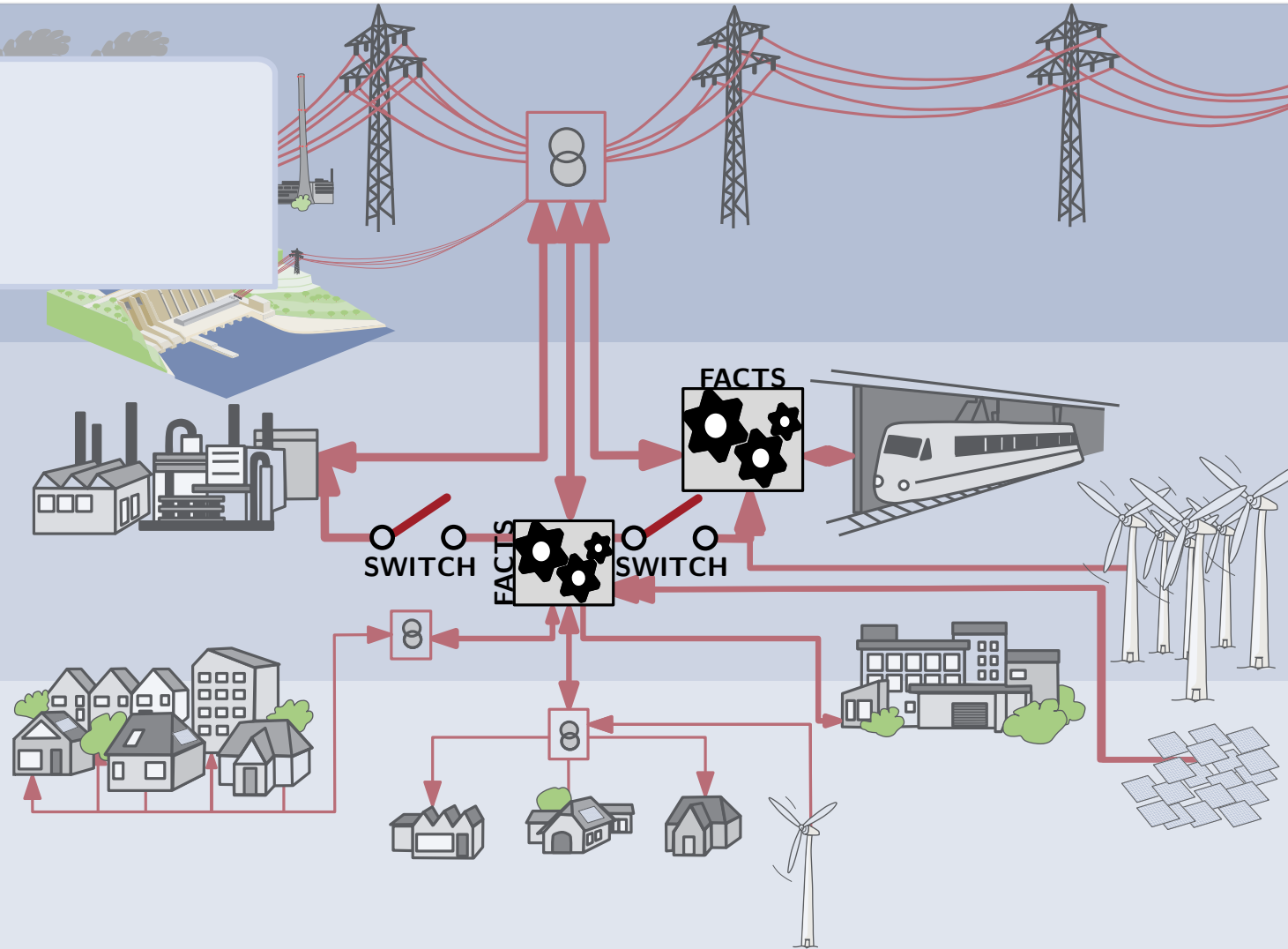
# Summary

Power Flows...

- Algorithms

Power Grid

Prosumer



# Summary

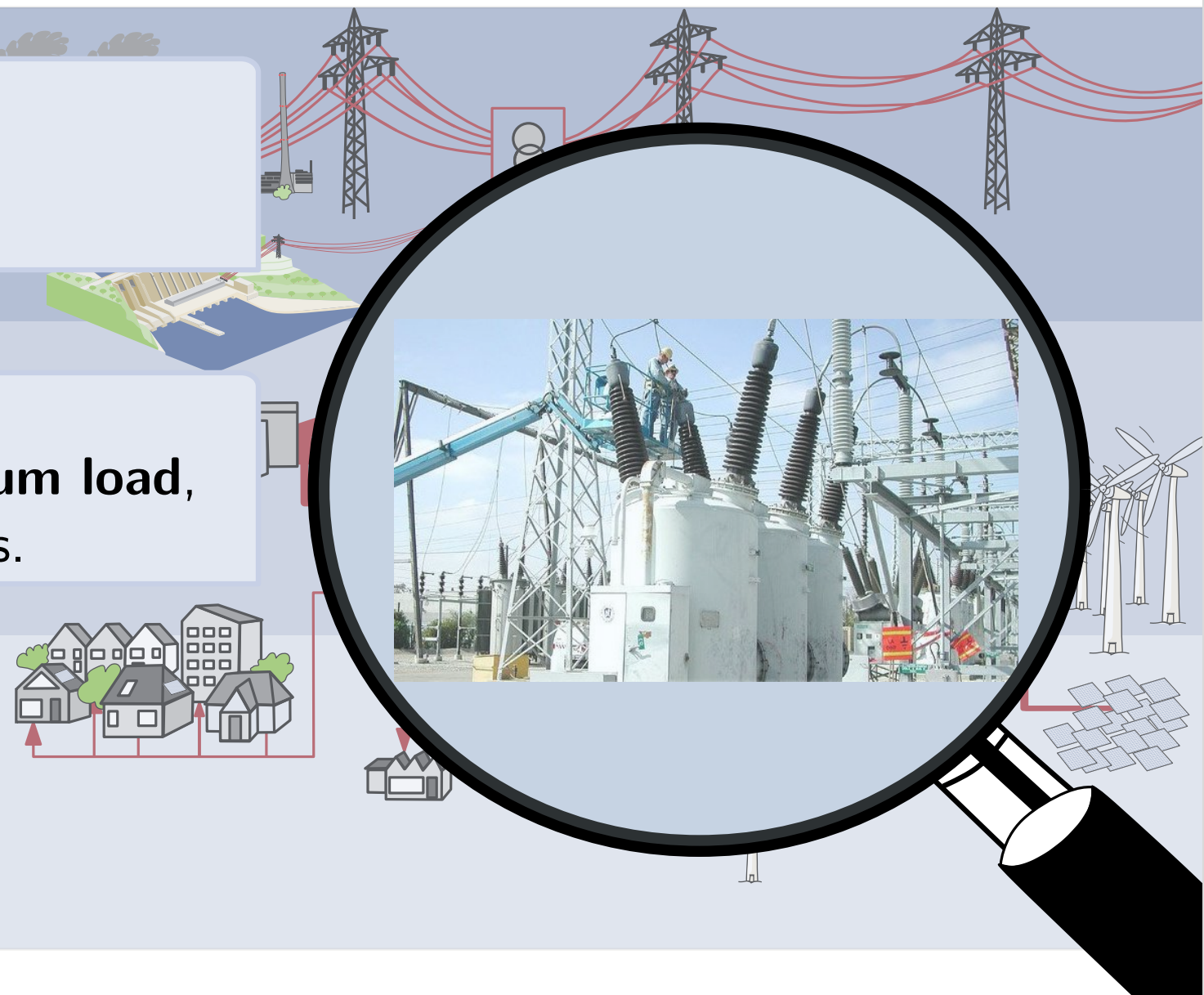
## Power Flows...

- Algorithms

## Switches...

- increase **maximum load**,
- are **control** units.

Prosumer





# Summary

## Power Flows...

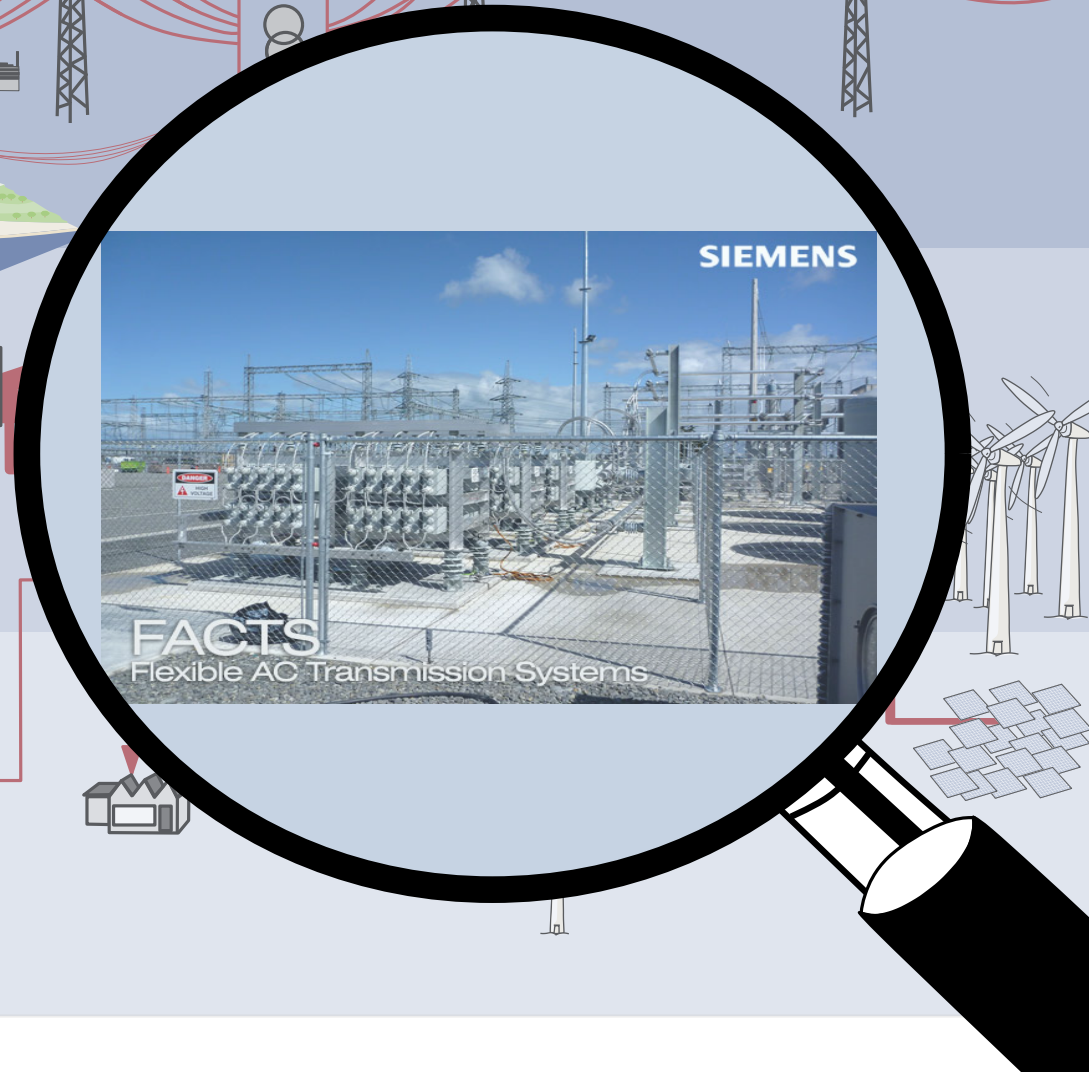
- Algorithms

## Switches...

- increase **maximum load**,
- are **control** units.

## FACTS...

- increase **maximum load**,
- are **control** units,
- are **expensive**.



# Acknowledgment

I am thankful for the questions, discussions, reading, comments, and support of...



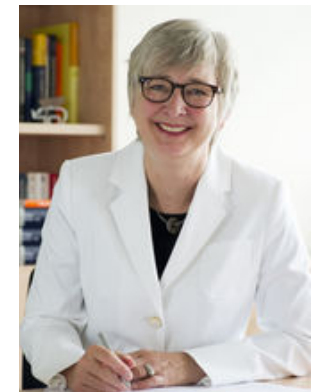
**Matthias Wolf**



**Marc Timme**



**Guido Brückner**



**Dorothea Wagner**



**Torsten Ueckerdt**

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