

A subexponential lower bound for Zadeh's pivoting rule for solving linear programs and games

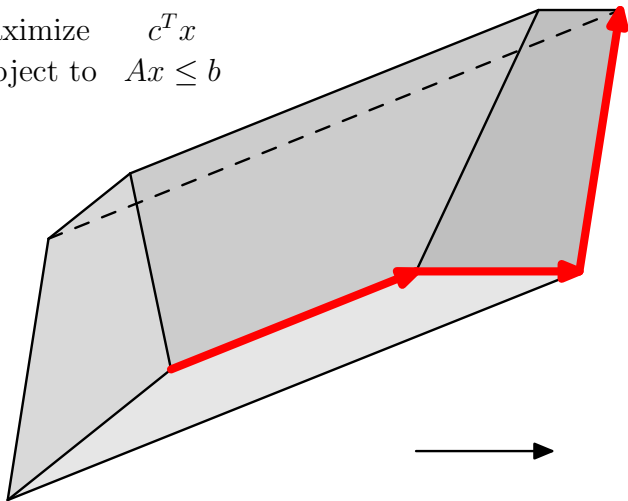
Oliver Friedmann

Department of Computer Science,
Ludwig-Maximilians-Universität Munich, Germany.

Linear Programming and Simplex

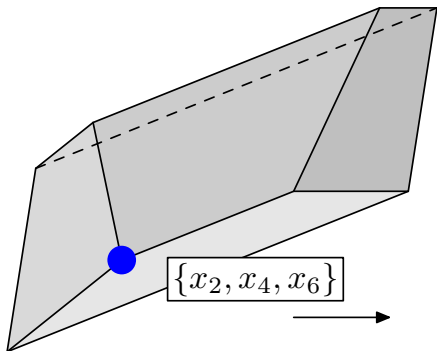
The simplex algorithm, Dantzig (1947)

$$\begin{array}{ll} \text{maximize} & c^T x \\ \text{subject to} & Ax \leq b \end{array}$$



Basic feasible solutions and pivoting

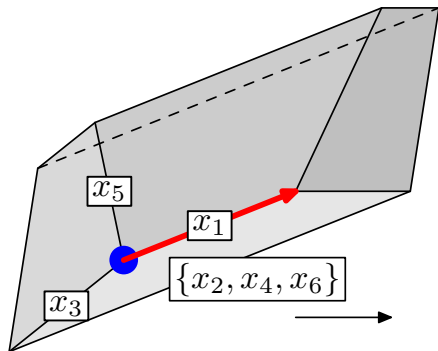
$$\begin{aligned}
 \max \quad & 2x_1 - 2x_3 - 2x_5 - x_6 \\
 \text{s.t.} \quad & \frac{1}{3}x_1 + x_2 - \frac{2}{3}x_3 - \frac{2}{3}x_5 = 1 \\
 & x_3 + x_4 - x_6 = 1 \\
 & x_5 + x_6 = 1 \\
 & x_1, x_2, x_3, x_4, x_5, x_6 \geq 0
 \end{aligned}$$



- The corners of the polytope correspond to **basic feasible solutions**: At most n , the number of equality constraints, variables are non-zero. The non-zero variables, or *basic* variables, form a *basis*.
- Moving along an edge corresponds to **pivoting**: Exchange a variable in the basis with a non-basic variable.

Basic feasible solutions and pivoting

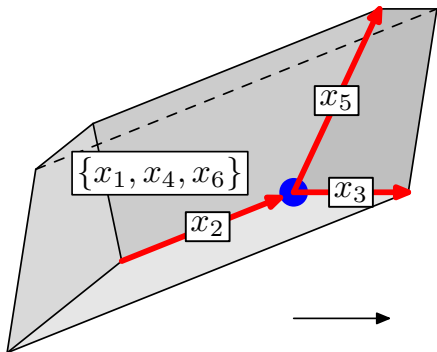
$$\begin{aligned}
 \max \quad & -1 + 2x_1 - 2x_3 - x_5 \\
 \text{s.t.} \quad & x_2 = 1 - \frac{1}{3}x_1 + \frac{2}{3}x_3 + \frac{2}{3}x_5 \\
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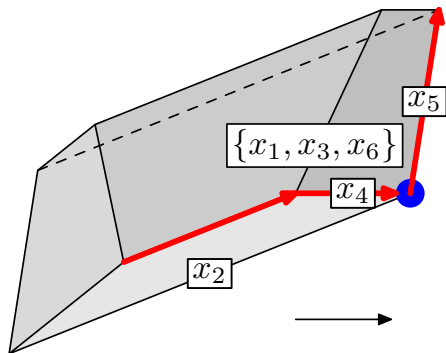
$$\begin{aligned}
 \max \quad & 5 - 6x_2 + 2x_3 + 3x_5 \\
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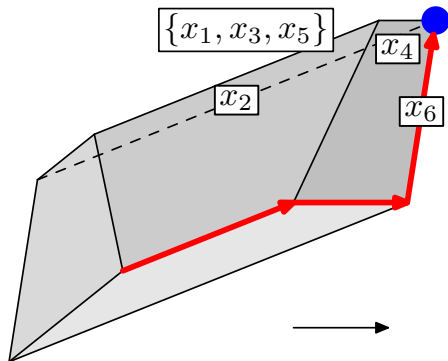
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Basic feasible solutions and pivoting

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Pivoting rules

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- **History-based** rules (this talk): We show that **Zadeh's LEAST-ENTERED** rule is subexponential.

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Our results have been obtained by using a deep relation between algorithmic game theory and linear programming.

On the diameter of polytopes

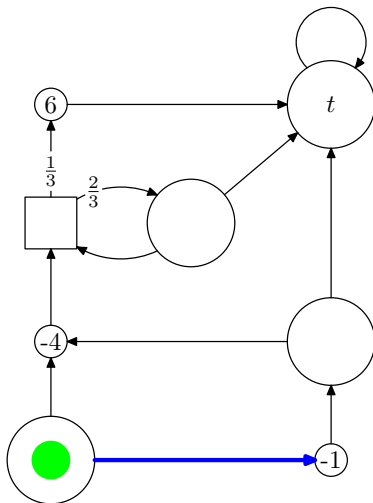
- Hirsch conjecture (1957): The diameter of any n -facet polytope in d -dimensional Euclidean space is at most $n - d$.

On the diameter of polytopes

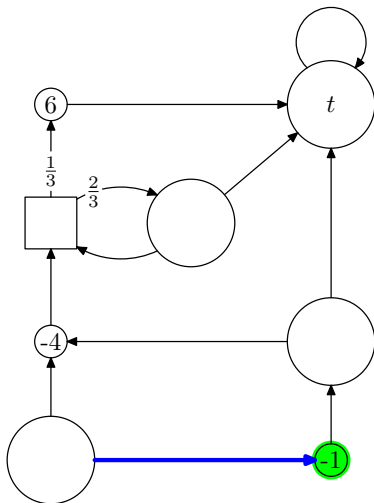
- Hirsch conjecture (1957): The diameter of any n -facet polytope in d -dimensional Euclidean space is at most $n - d$.
- Santos (2010): A counter-example to the Hirsch conjecture.
 - It remains open whether the diameter is polynomial, or even linear, in n and d .

Games and Policy Iteration

Markov decision processes (MDPs)

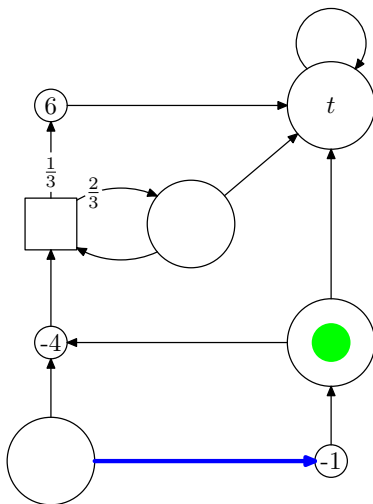


Markov decision processes (MDPs)



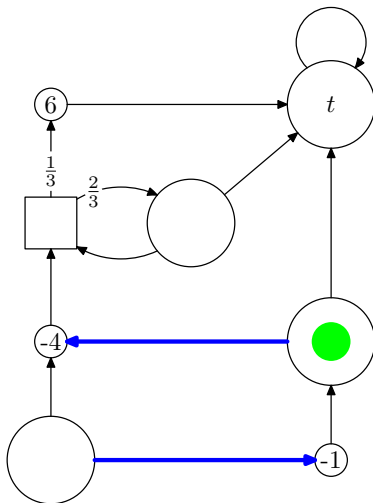
Reward: -1

Markov decision processes (MDPs)



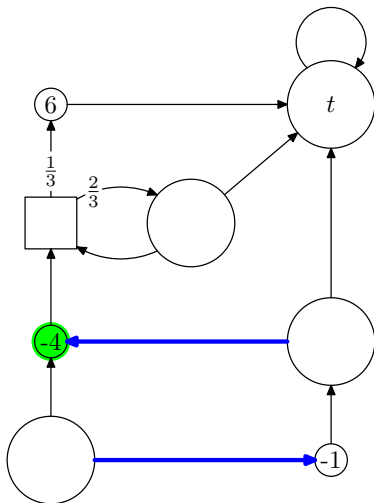
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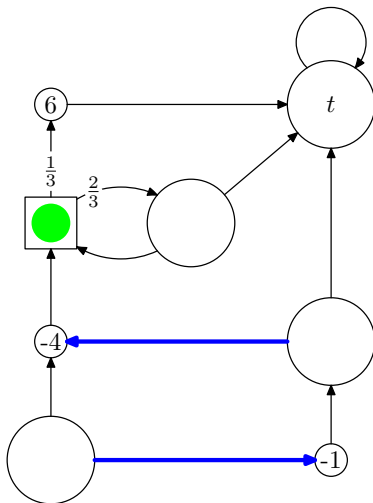
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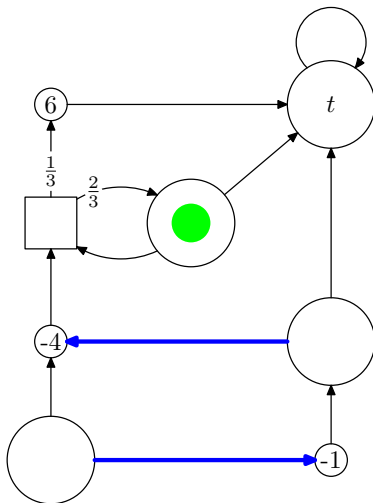
Reward: $-1 - 4$

Markov decision processes (MDPs)



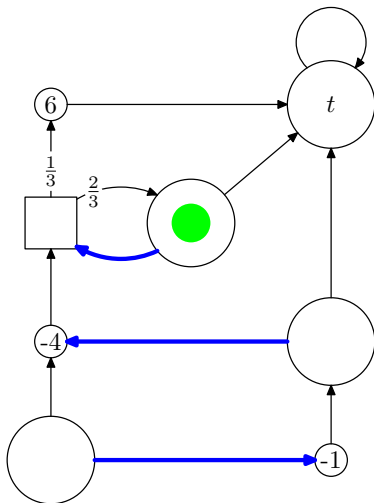
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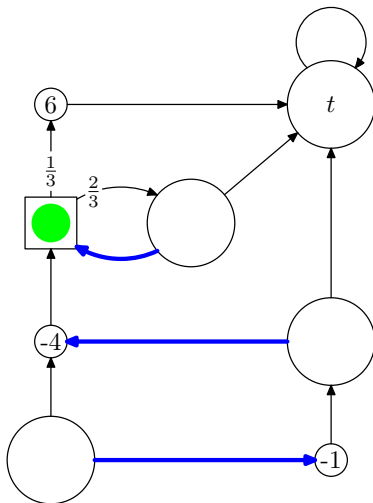
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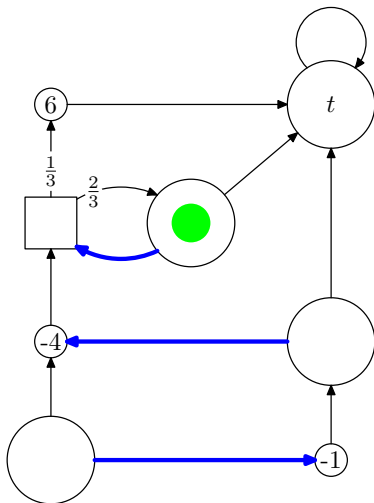
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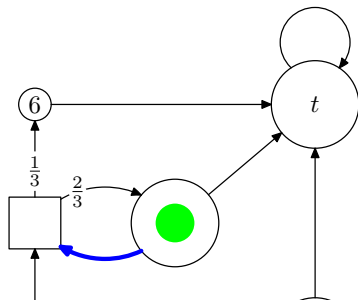
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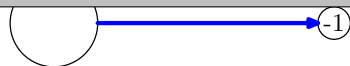
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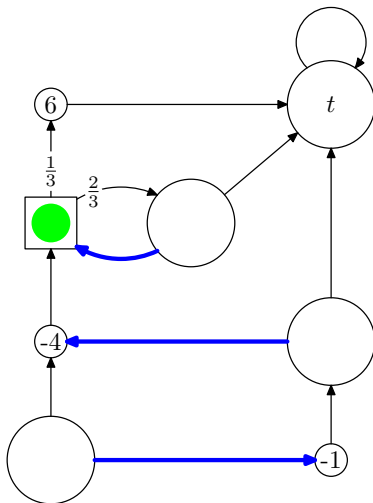
Shapley (1953), Bellman (1957):

There exists an optimal history-independent choice from each state.



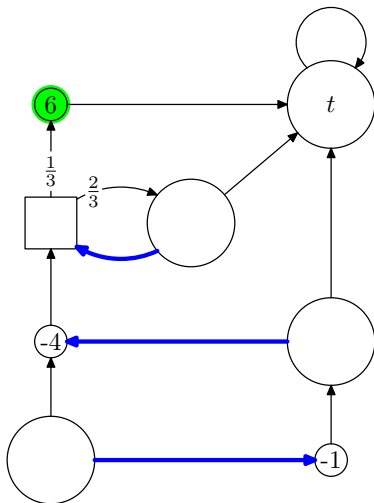
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Markov decision processes (MDPs)



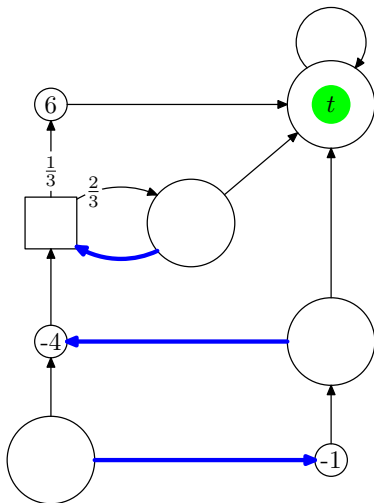
Reward: $-1 - 4$

Markov decision processes (MDPs)



Reward: $-1 - 4 + 6$

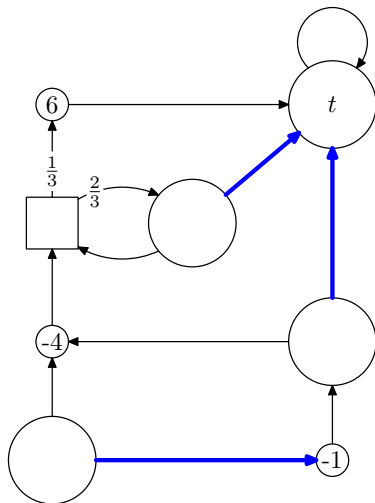
Markov decision processes (MDPs)



$$\text{Reward: } -1 - 4 + 6 = 1$$

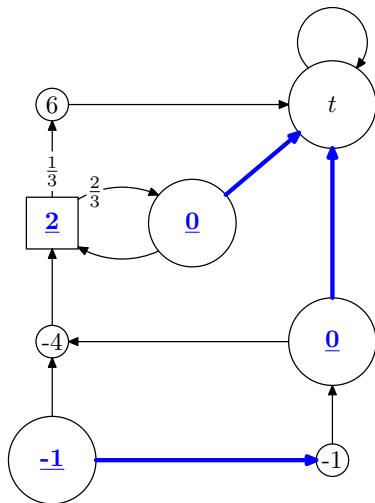
Policies and corresponding values

- A policy π is a choice of an action from each state.



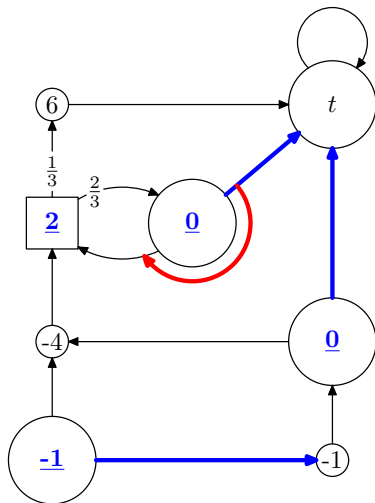
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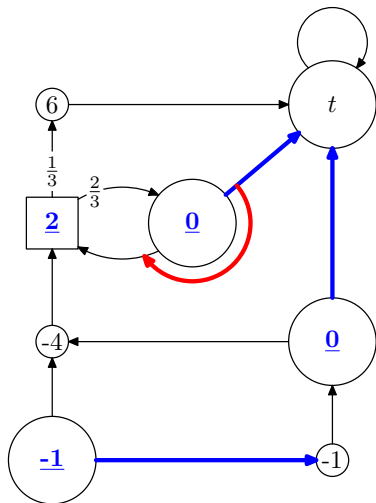
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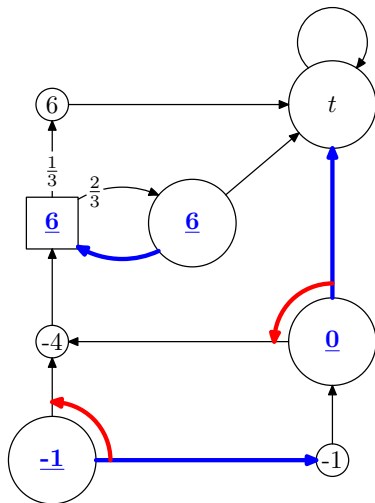
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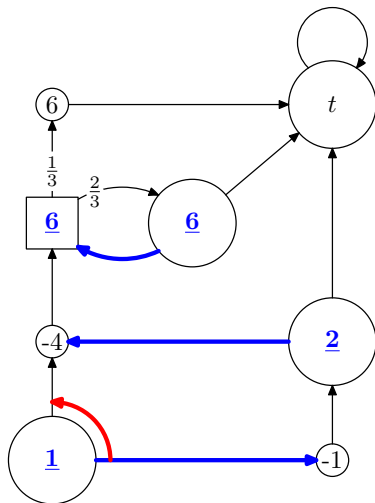
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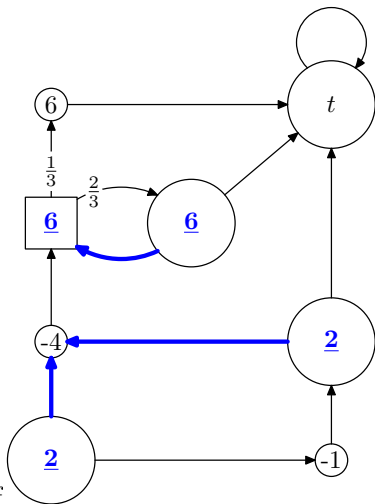
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- It suffices to check whether an action is improving for one step w.r.t. the current values.
- A policy π^* is optimal iff there are no improving switches. Optimal policies simultaneously maximize the values of all states.



MDPs and linear programming

- No improving switches for optimal policy π^* :

$$\forall i \in S : \text{VAL}_{\pi^*}(i) = \max_{a \in A_i} r_a + \sum_{j \in S} p_{a,j} \text{VAL}_{\pi^*}(j)$$

where A_i is the set of actions from state i , r_a is the expected reward of using action a , and $p_{a,j}$ is the probability of moving to state j when using action a .

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- This can be used to formulate an LP for solving the MDP:

$$\begin{aligned} & \text{minimize} \quad \sum_{i \in S} v_i \\ & \text{s.t.} \quad \forall i \in S \forall a \in A_i : v_i \geq r_a + \sum_{j \in S} p_{a,j} v_j \end{aligned}$$

Primal and dual LPs for MDPs

$$\text{minimize } \sum_{i \in S} v_i$$

$$s.t. \quad \forall i \in S \quad \forall a \in A_i : v_i \geq r_a + \sum_{j \in S} p_{a,j} v_j$$

$$\text{maximize } \sum_{i \in S} \sum_{a \in A_i} r_a x_a$$

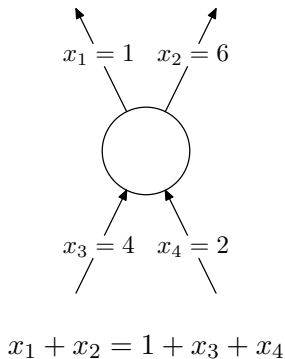
$$s.t. \quad \forall i \in S : \sum_{a \in A_i} x_a = 1 + \sum_{j \in S} \sum_{a \in A_j} p_{a,i} x_a$$

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Flow conservation:



Primal and dual LPs for MDPs

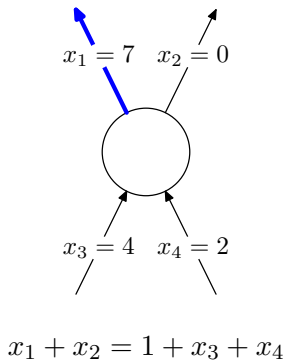
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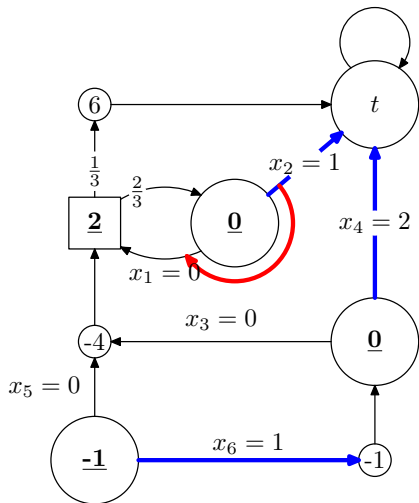
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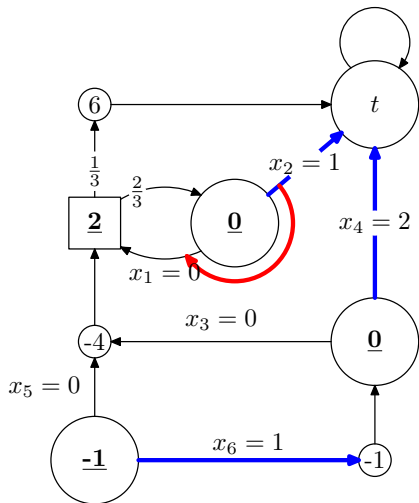
- Every basic feasible solution corresponds to a policy π .

Variables of the primal LP



- x_a is the expected number of times action a is used, summed over all starting states.

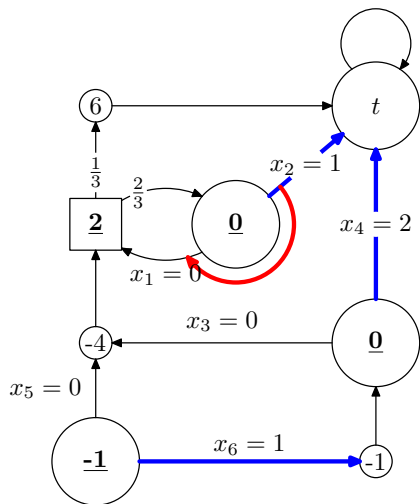
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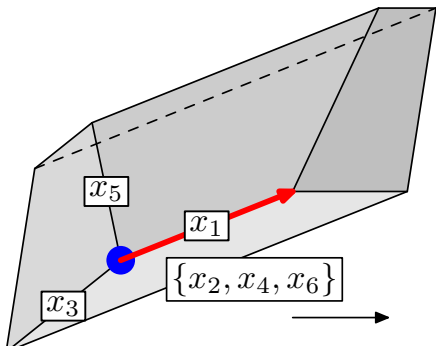
- x_a is the expected number of times action a is used, summed over all starting states.
- We have:

$$\sum_{i \in S} \text{VAL}_\pi(i) = \sum_{a \in \pi} r_a x_a^\pi$$

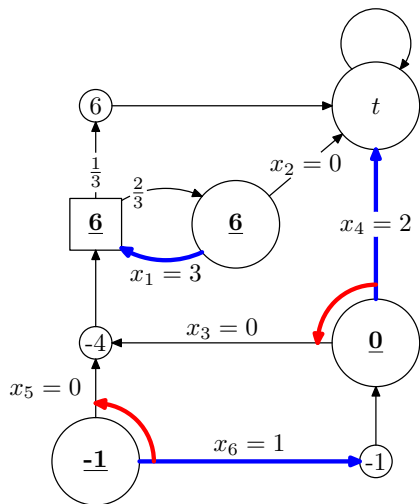
From MDP to LP



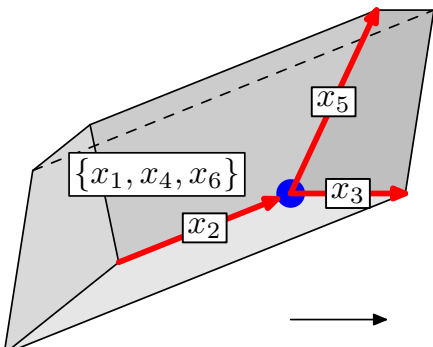
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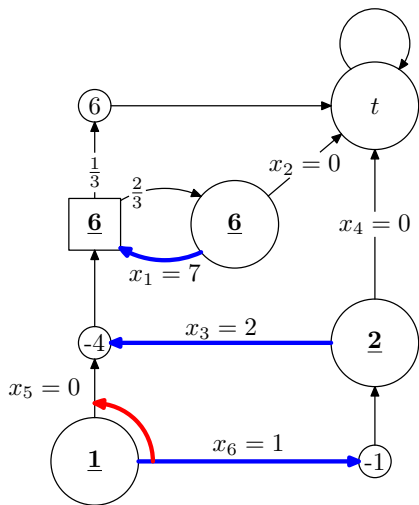
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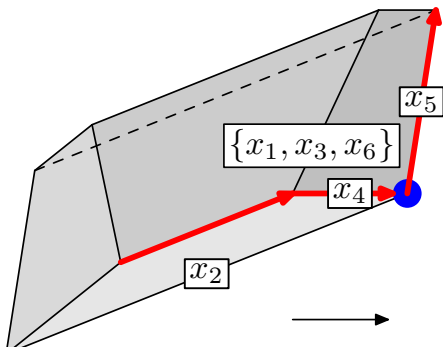
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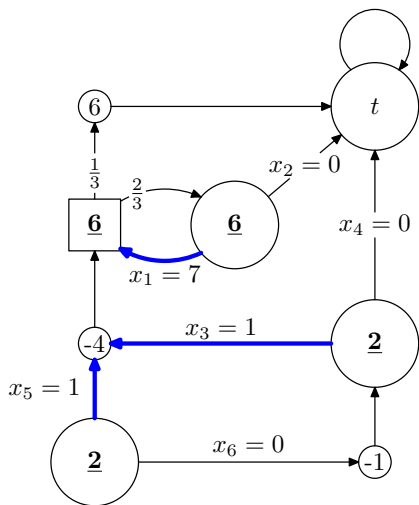
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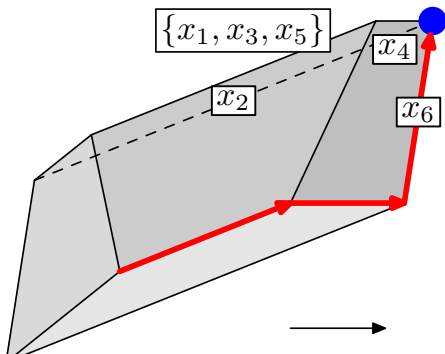
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Diameter

Question: **theoretically** possible to have polynomially many iterations?

Let G be a Markov decision process and n be the number of nodes.

Definition: the **diameter** of G is the **least number of iterations** required to solve G

Small Diameter Theorem

The diameter of G is **less or equal to n** .

Lower Bound for Zadeh's Rule

Lower bound construction

- We define a family of lower bound MDPs G_n such that the LEAST-ENTERED pivoting rule will simulate an n -bit binary counter.

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- We make use of exponentially growing rewards (and penalties): To get a higher reward the MDP is willing to sacrifice everything that has been built up so far.

Lower bound construction

- We define a family of lower bound MDPs G_n such that the LEAST-ENTERED pivoting rule will simulate an n -bit binary counter.
- We make use of exponentially growing rewards (and penalties): To get a higher reward the MDP is willing to sacrifice everything that has been built up so far.
- Notation: Integer priority p corresponds to reward $(-N)^p$, where $N = 7n + 1$.

... < 5 < 3 < 1 < 2 < 4 < 6 < ...



Background

- The use of priorities is inspired by *parity games*.

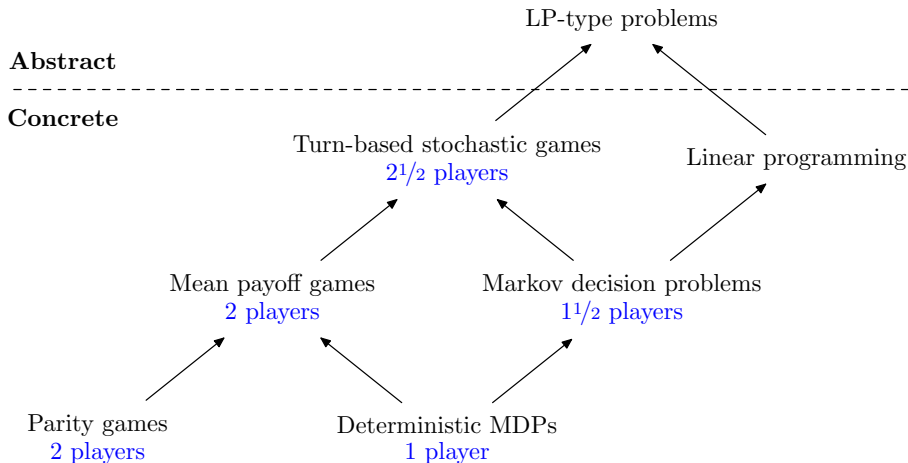
Background

- The use of priorities is inspired by *parity games*.
- Friedmann (2009): The strategy iteration algorithm may require exponentially many iterations to solve parity games.
- Fearnley (2010): The strategy iteration algorithm may require exponentially many iterations to solve MDPs.

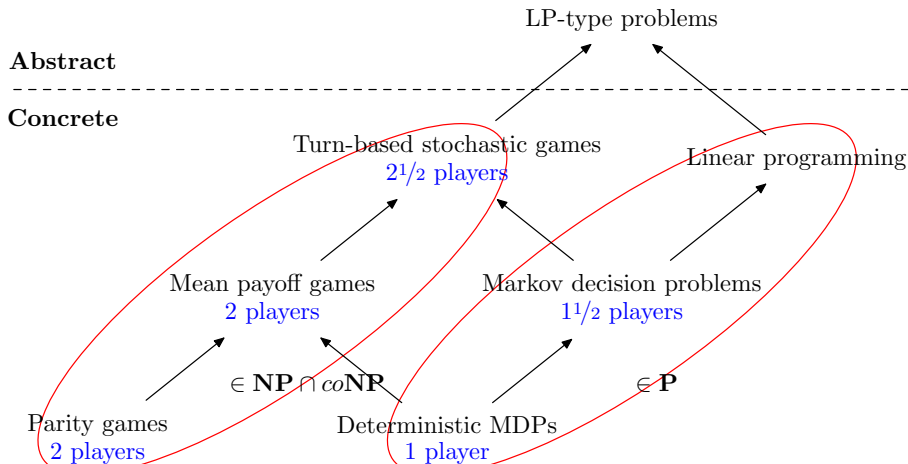
Background

- The use of priorities is inspired by *parity games*.
- Friedmann (2009): The strategy iteration algorithm may require exponentially many iterations to solve parity games.
- Fearnley (2010): The strategy iteration algorithm may require exponentially many iterations to solve MDPs.
- We also first proved a lower bound for parity games and then transferred the result to MDPs and linear programs.

Related game-theoretic settings



Related game-theoretic settings



Zadeh's pivoting rule

Zadeh's LEAST-ENTERED rule

Perform single switch that has been applied **least often**.

Dear Victor,

Please post this offer of \$1000 to the first person who can find a counterexample to the least entered rule or prove it to be polynomial. The least entered rule enters the improving variable which has been entered least often.

Sincerely,

Norman Zadeh

(taken from David Avis' paper)

Tie-Breaking Rule

Tie-Breaking Rule = method of selecting a switch in case of a tie (w.r.t. the occurrence record)

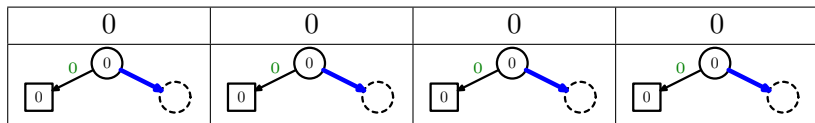
Proof of **Small Diameter Theorem** implies:

Corollary

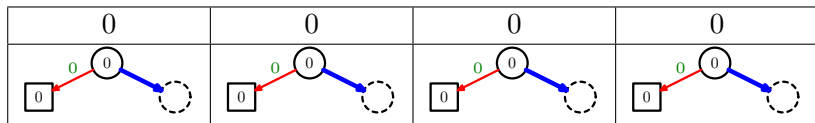
There is a tie-breaking rule s.t. Zadeh's rule requires linearly many iterations in the worst-case.

Consequence: lower bound construction is equipped with particular tie-breaking rule

Binary Counting

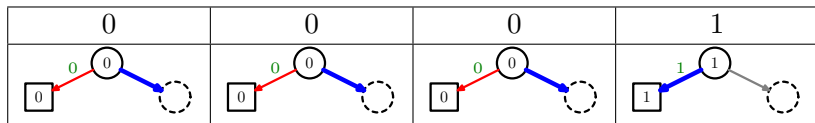


Binary Counting



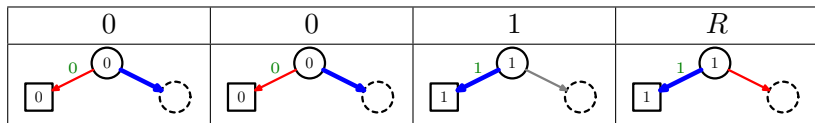
Principle: If a bit can be set, then all bits can be set.

Binary Counting



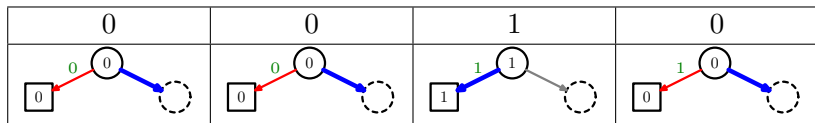
Tie-Breaking: We decide to set the first bit.

Binary Counting



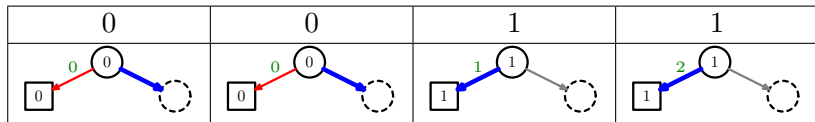
Set the second bit and **reset** the first bit.

Binary Counting



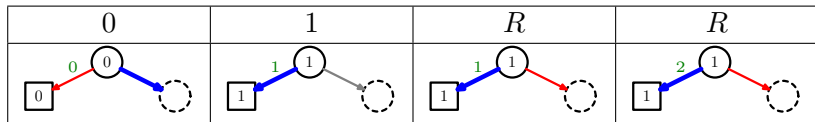
Set the first bit again.

Binary Counting



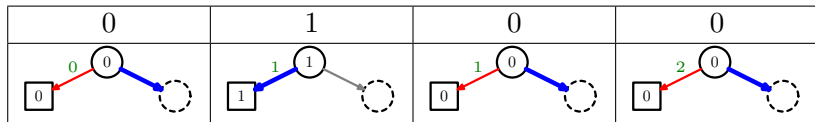
Continue...

Binary Counting



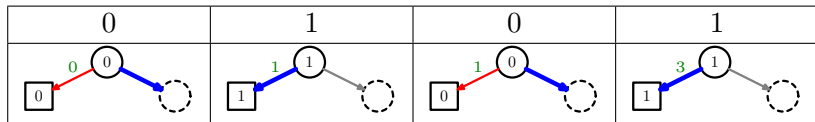
Continue...

Binary Counting



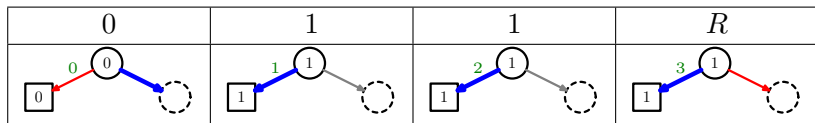
Continue...

Binary Counting



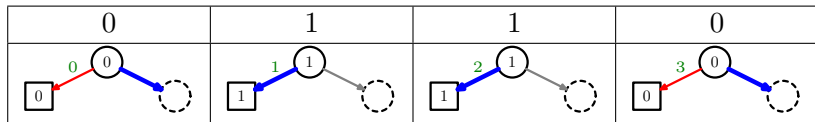
Continue...

Binary Counting



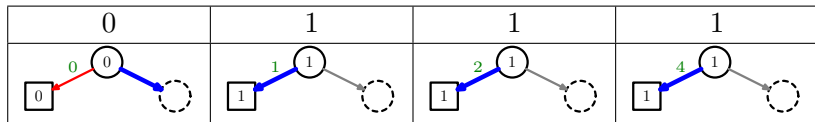
Continue...

Binary Counting



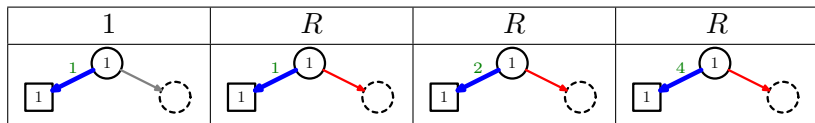
Continue...

Binary Counting



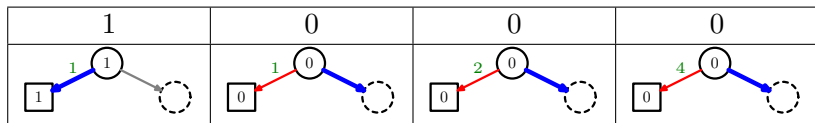
Continue...

Binary Counting



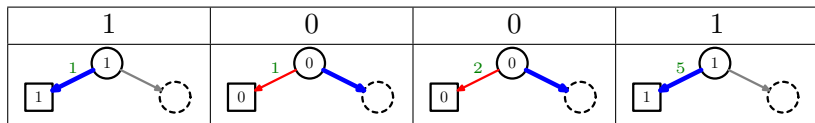
Continue...

Binary Counting



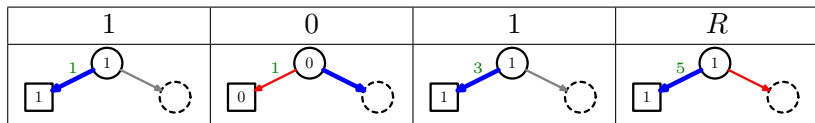
Continue...

Binary Counting



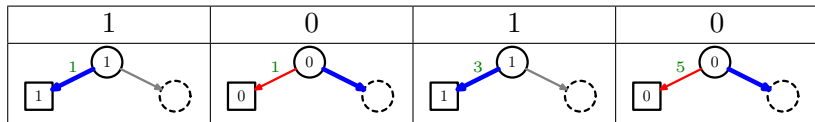
Continue...

Binary Counting



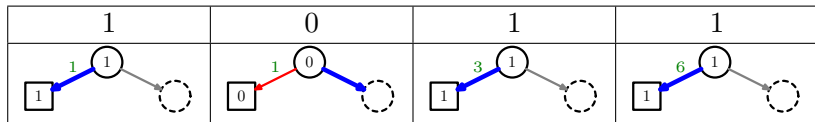
Continue...

Binary Counting



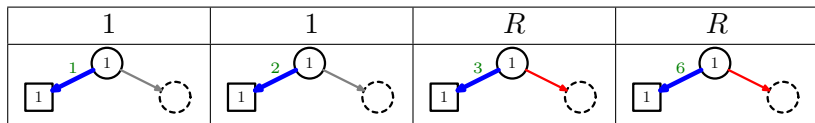
Continue...

Binary Counting



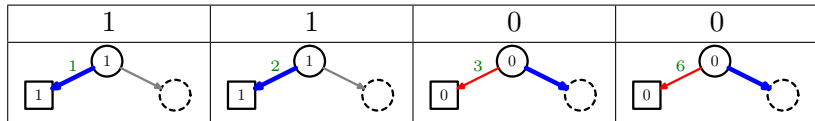
Continue...

Binary Counting



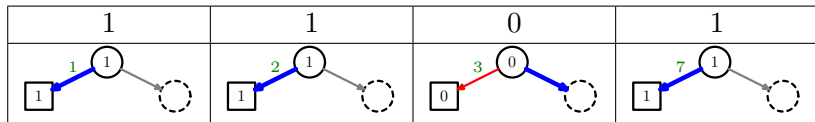
Continue...

Binary Counting



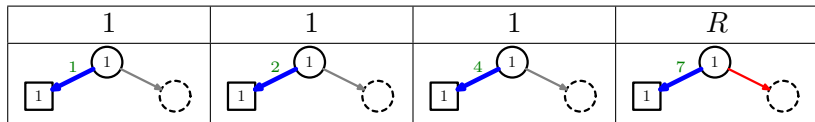
Continue...

Binary Counting



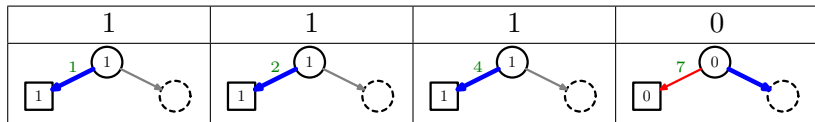
Continue...

Binary Counting



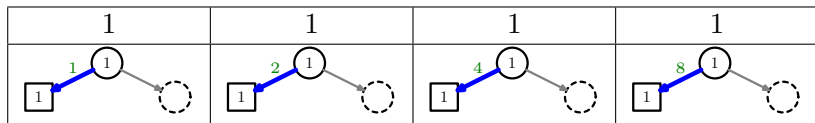
Continue...

Binary Counting



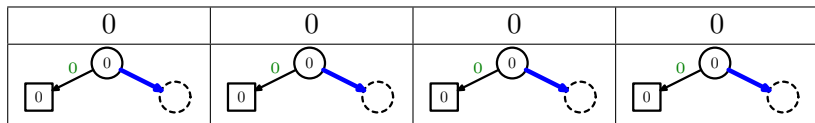
Continue...

Binary Counting



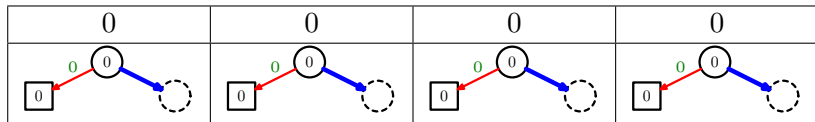
Problem: Occurrence record unbalanced!

Binary Counting (... again!)



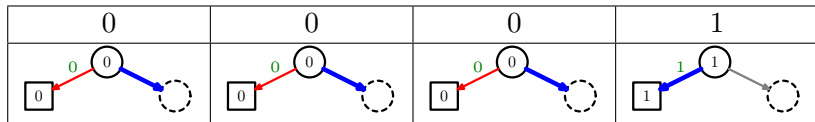
Let's do it again - watch the occurrence record this time!

Binary Counting (... again!)



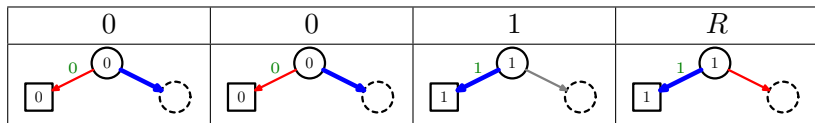
Everything okay so far...

Binary Counting (... again!)



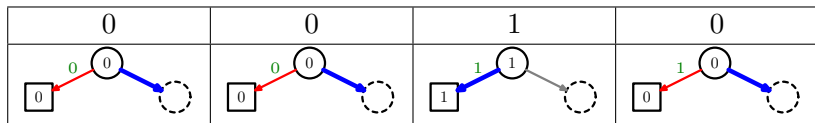
Everything okay so far...

Binary Counting (... again!)



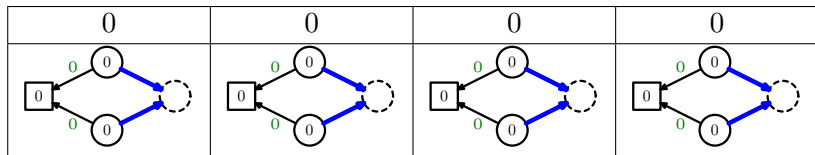
Everything okay so far...

Binary Counting (... again!)



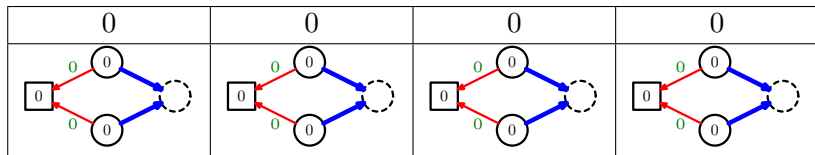
Problem: We **have** to set one of the higher bits now!

Binary Counting with conjunctive bits



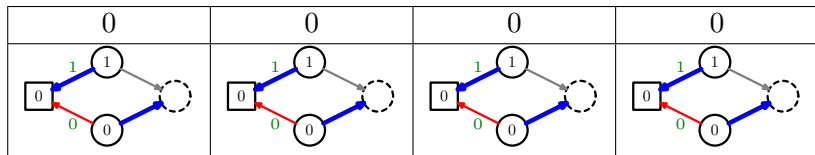
Replace gadget by **two-bit, conjunctive** structure.

Binary Counting with conjunctive bits



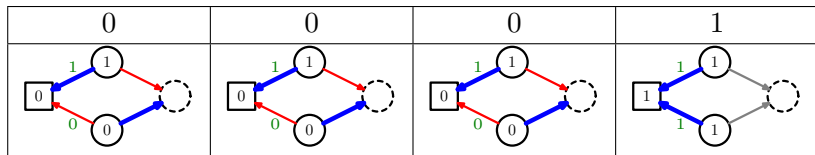
Gadget is **set** iff **both edges** are going in.

Binary Counting with conjunctive bits



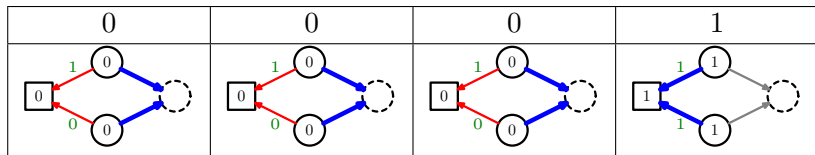
Set one improving edge of every gadget.

Binary Counting with conjunctive bits



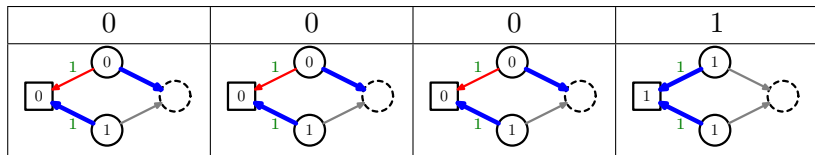
Set other improving edge of first gadget.

Binary Counting with conjunctive bits



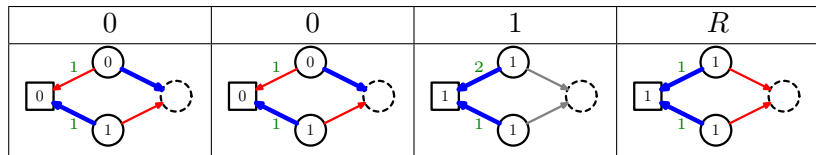
Other gadgets have updated to their old setting.

Binary Counting with conjunctive bits



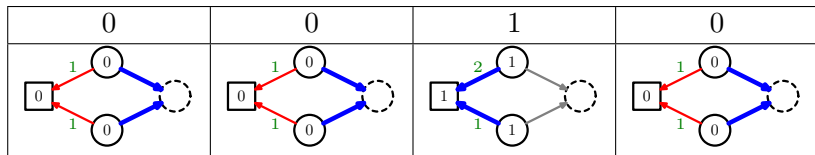
Set one improving edge of every gadget again.

Binary Counting with conjunctive bits



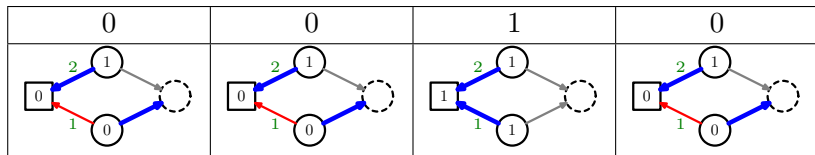
Set other improving edge of second gadget.

Binary Counting with conjunctive bits



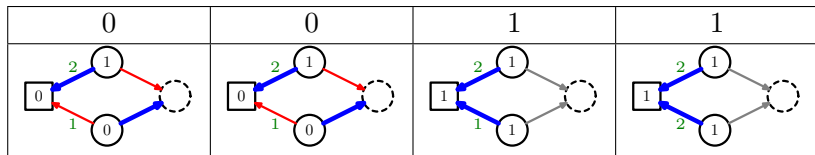
Reset all other gadgets.

Binary Counting with conjunctive bits



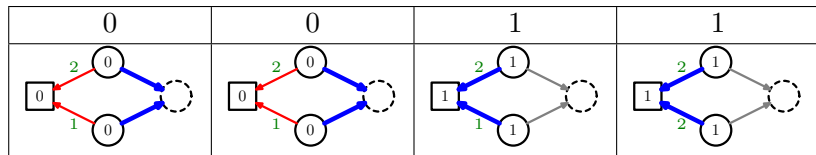
Everything okay so far, continue...

Binary Counting with conjunctive bits



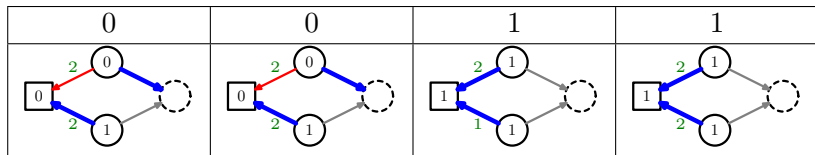
Everything okay so far, continue...

Binary Counting with conjunctive bits



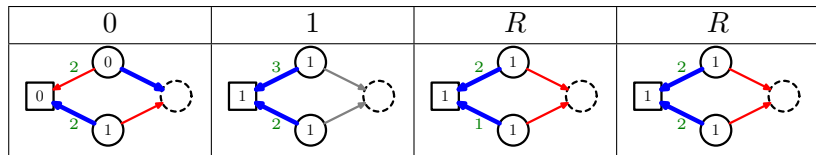
Everything okay so far, continue...

Binary Counting with conjunctive bits



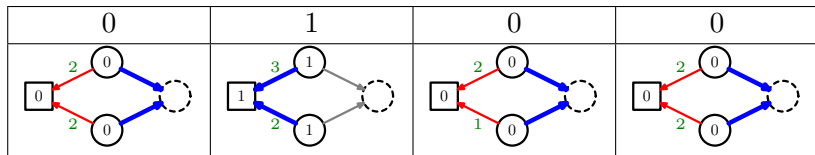
Everything okay so far, continue...

Binary Counting with conjunctive bits



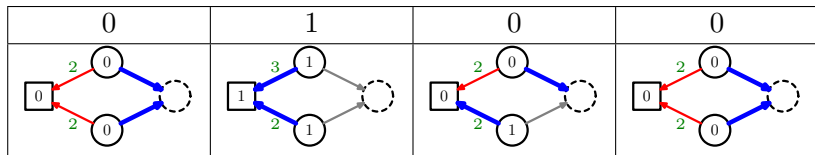
Everything okay so far, continue...

Binary Counting with conjunctive bits



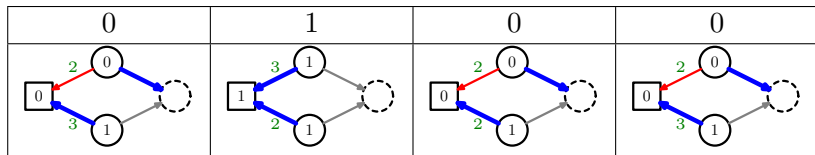
Everything okay so far, continue...

Binary Counting with conjunctive bits



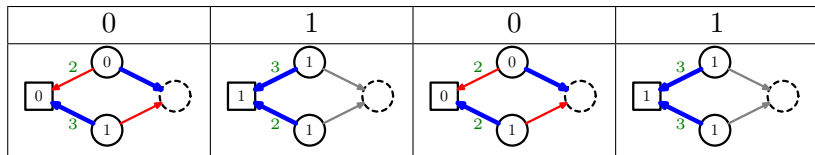
Everything okay so far, continue...

Binary Counting with conjunctive bits



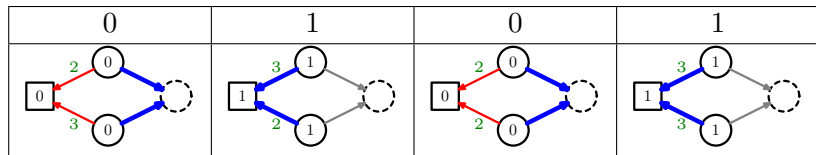
Everything okay so far, continue...

Binary Counting with conjunctive bits



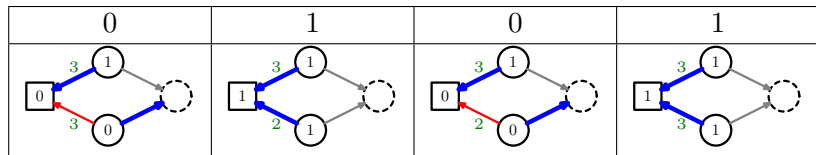
Everything okay so far, continue...

Binary Counting with conjunctive bits



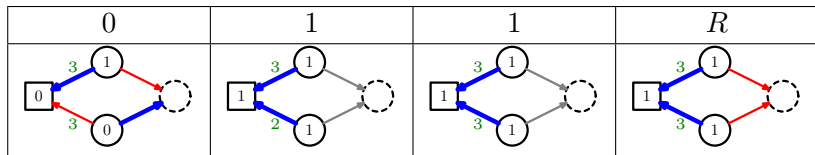
Everything okay so far, continue...

Binary Counting with conjunctive bits



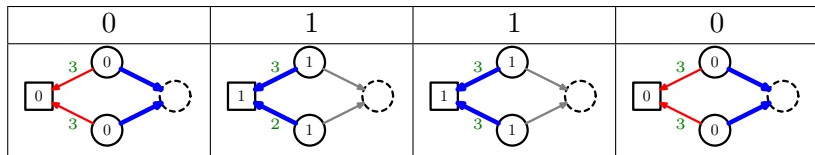
Everything okay so far, continue...

Binary Counting with conjunctive bits



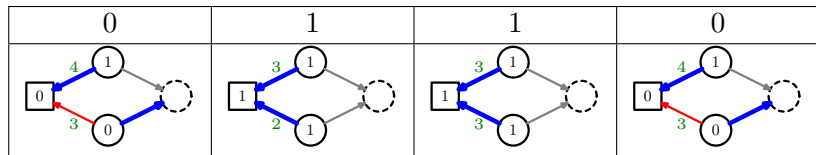
Everything okay so far, continue...

Binary Counting with conjunctive bits



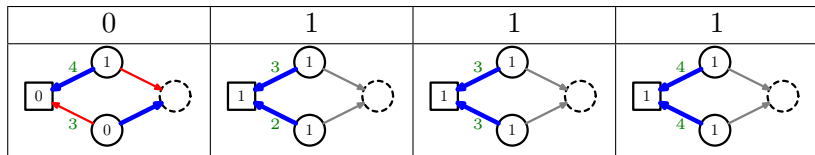
Everything okay so far, continue...

Binary Counting with conjunctive bits



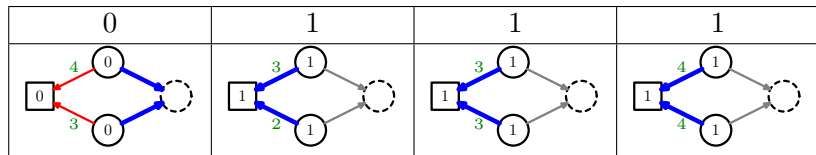
Everything okay so far, continue...

Binary Counting with conjunctive bits



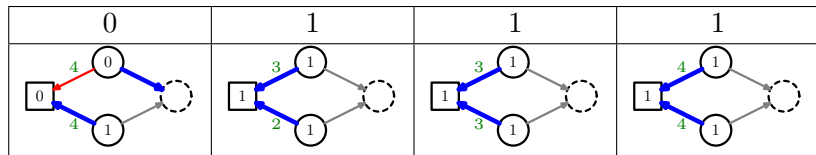
Everything okay so far, continue...

Binary Counting with conjunctive bits



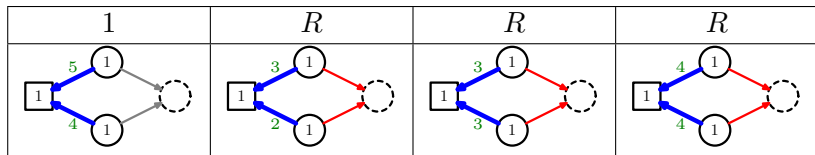
Everything okay so far, continue...

Binary Counting with conjunctive bits



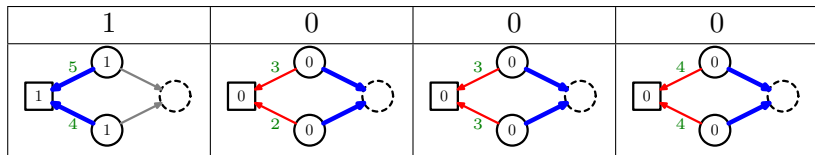
Everything okay so far, continue...

Binary Counting with conjunctive bits



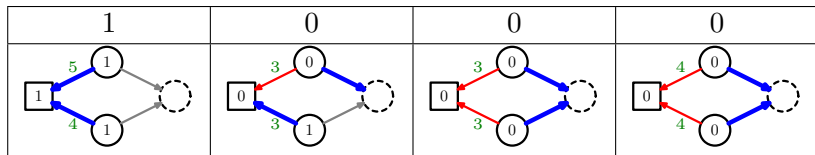
Reset all three lower gadgets.

Binary Counting with conjunctive bits



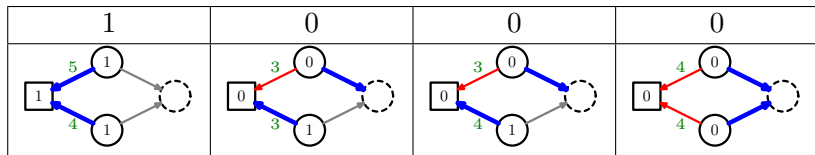
Occurrence record of gadget #3 is pretty low...

Binary Counting with conjunctive bits



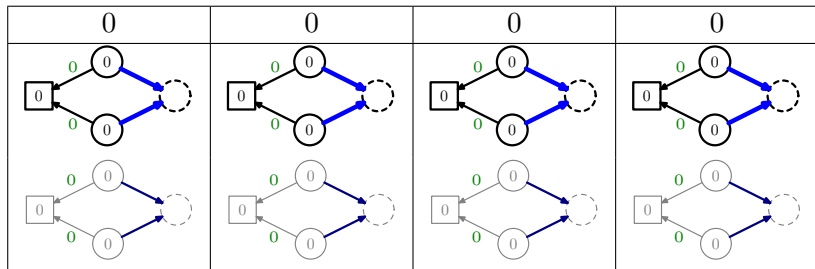
Occurrence record of gadget #3 is pretty low...

Binary Counting with conjunctive bits



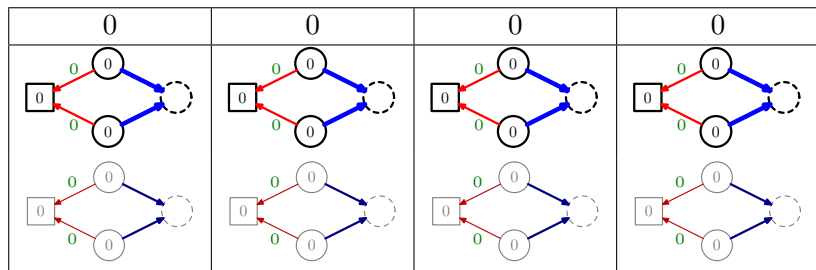
Problem: We **have** to set gadget #2 or #3 now!

Binary Counting with conjunctive representatives



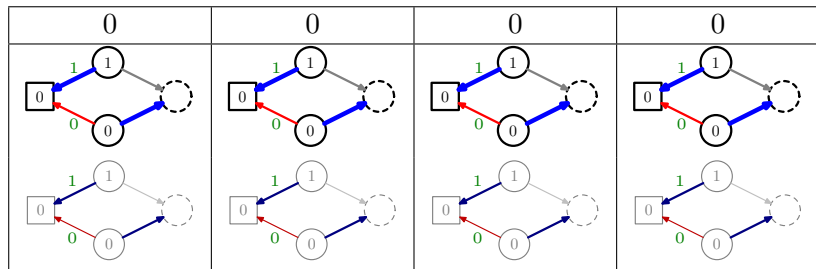
Replace gadget by **two** conjunctive structures.

Binary Counting with conjunctive representatives



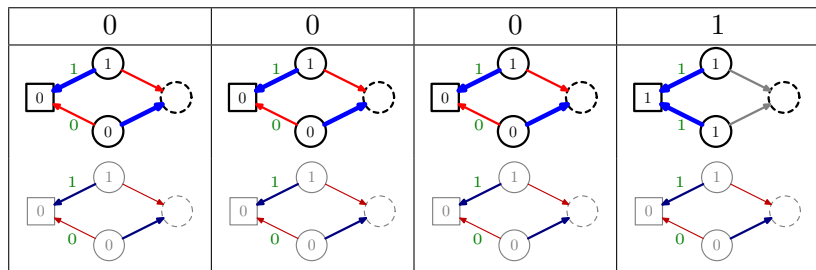
Only one representative subgadget is **active**. The **upper** representative is **active** iff the **next higher bit** is **not set**

Binary Counting with conjunctive representatives



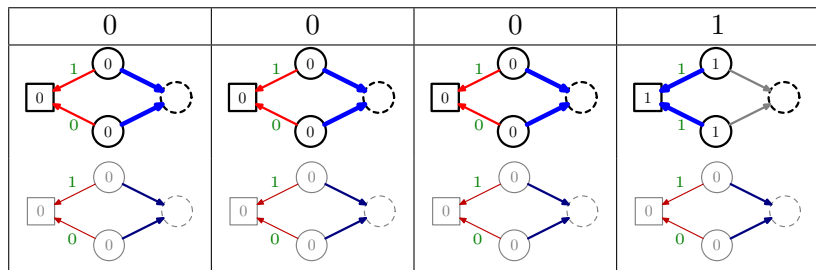
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Binary Counting with conjunctive representatives



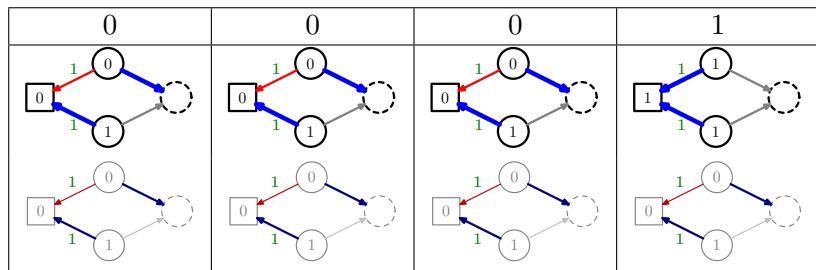
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Binary Counting with conjunctive representatives



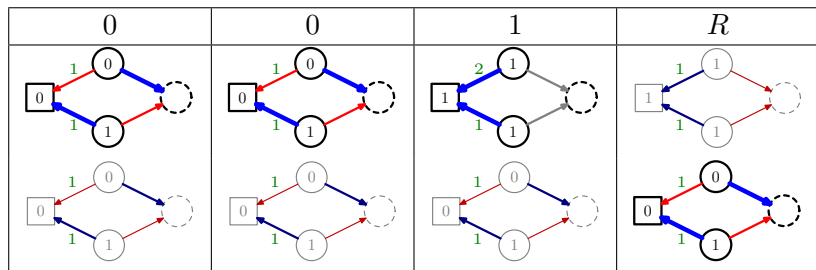
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Binary Counting with conjunctive representatives



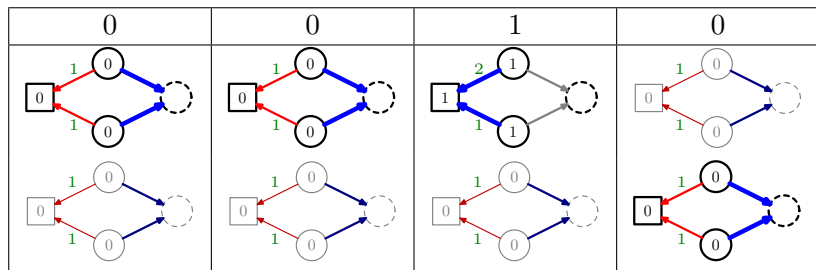
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Binary Counting with conjunctive representatives



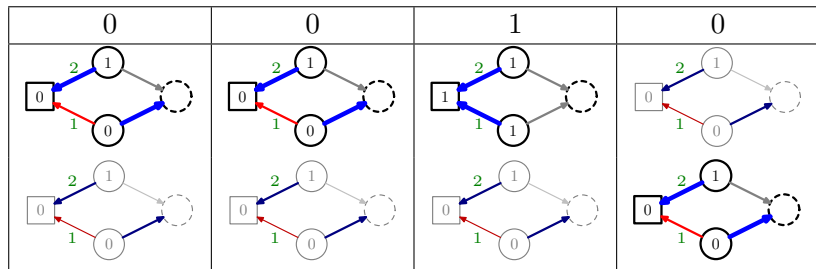
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Binary Counting with conjunctive representatives



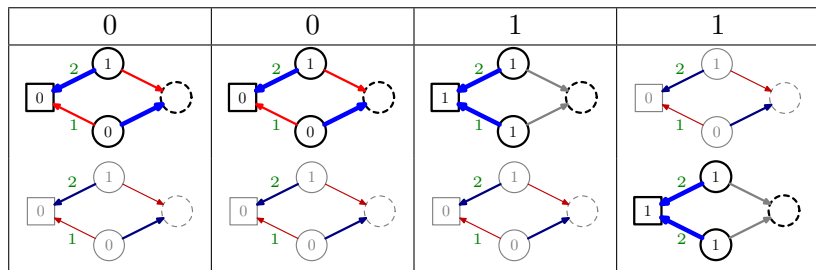
Only one representative subgadget is **active**. The **upper** representative is **active** iff the **next higher bit** is **not set**

Binary Counting with conjunctive representatives



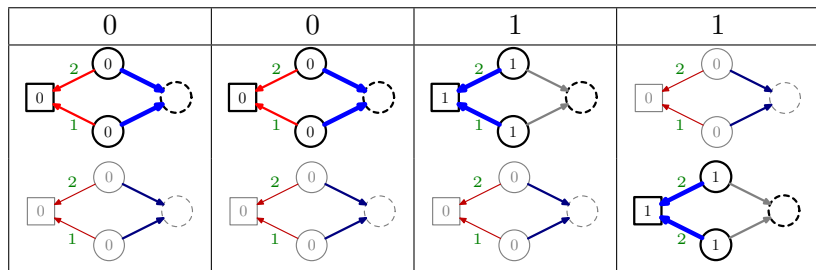
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Binary Counting with conjunctive representatives



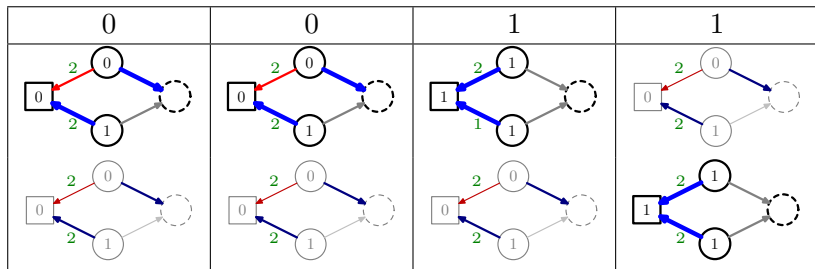
Only one representative subgadget is **active**. The **upper** representative is **active** iff the **next higher bit** is **not set**

Binary Counting with conjunctive representatives



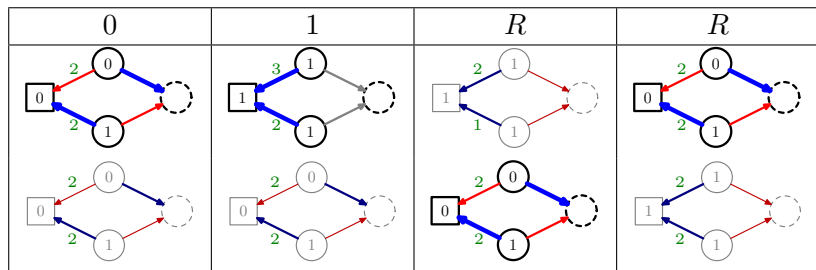
Only one representative subgadget is **active**. The **upper** representative is **active** iff the **next higher bit** is **not set**

Binary Counting with conjunctive representatives



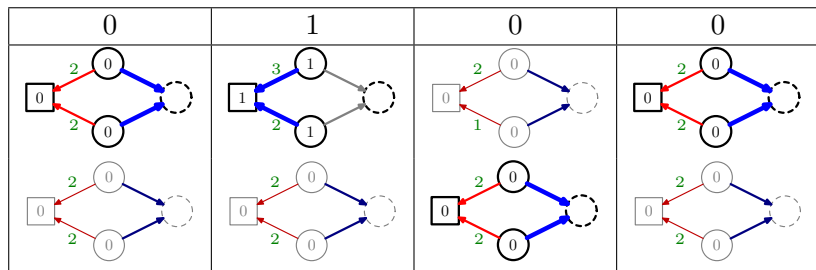
Only one representative subgadget is **active**. The **upper** representative is **active** iff the **next higher bit** is **not set**

Binary Counting with conjunctive representatives



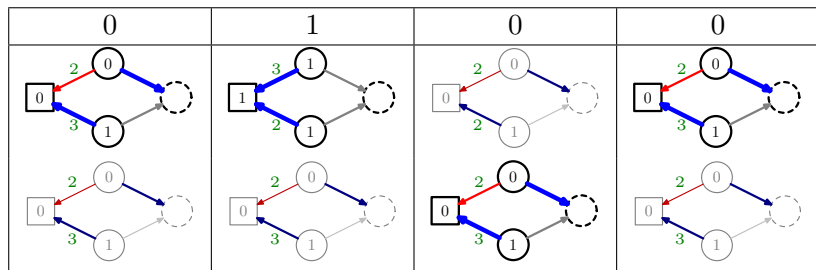
Only one representative subgadget is **active**. The **upper** representative is **active** iff the **next higher bit** is **not set**

Binary Counting with conjunctive representatives



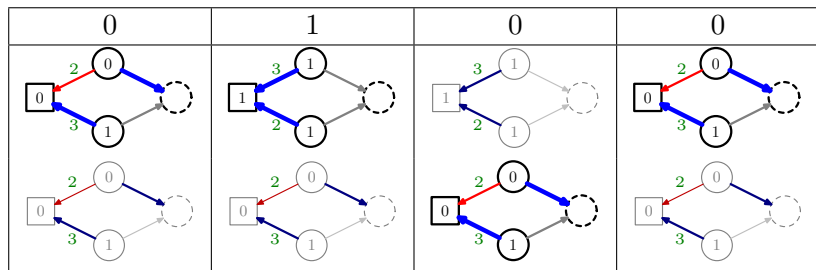
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Binary Counting with conjunctive representatives



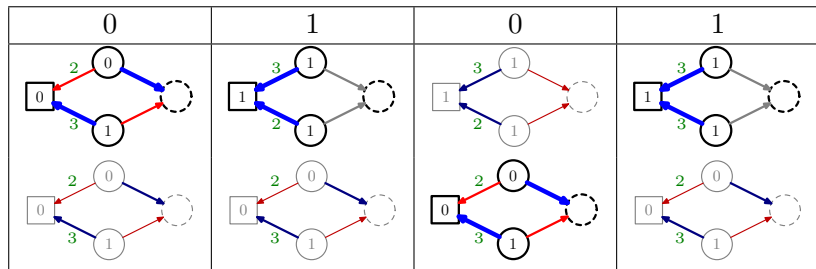
Only one representative subgadget is **active**. The **upper** representative is **active** iff the **next higher bit** is **not set**

Binary Counting with conjunctive representatives



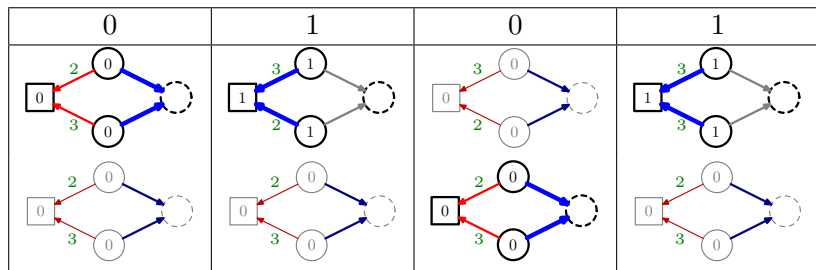
Only one representative subgadget is **active**. The **upper** representative is **active** iff the **next higher bit** is **not set**

Binary Counting with conjunctive representatives



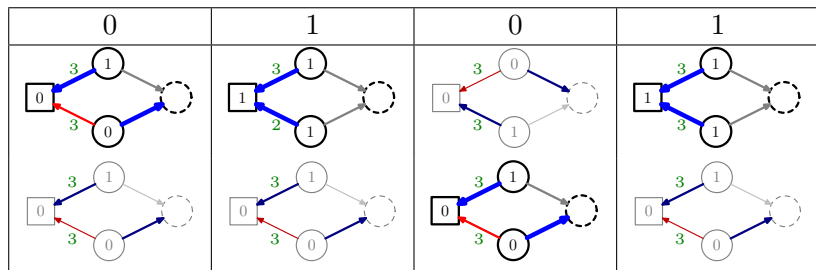
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Binary Counting with conjunctive representatives



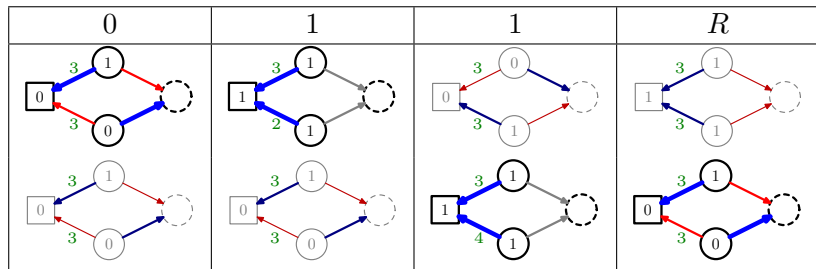
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Binary Counting with conjunctive representatives



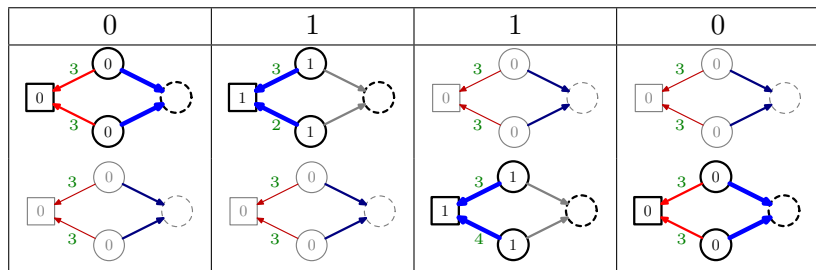
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Binary Counting with conjunctive representatives



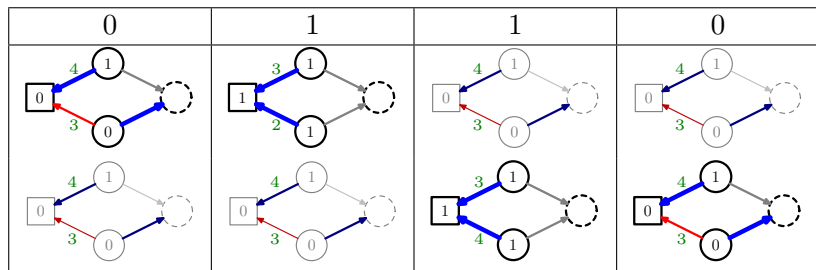
Only one representative subgadget is **active**. The **upper** representative is **active** iff the **next higher bit** is **not set**

Binary Counting with conjunctive representatives



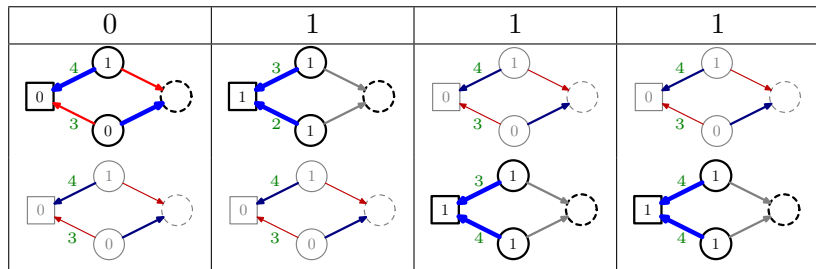
Only one representative subgadget is **active**. The **upper** representative is **active** iff the **next higher bit** is **not set**

Binary Counting with conjunctive representatives



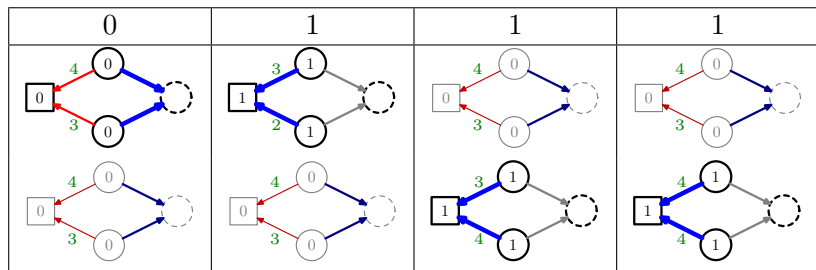
Only one representative subgadget is **active**. The **upper** representative is **active** iff the **next higher bit** is **not set**

Binary Counting with conjunctive representatives



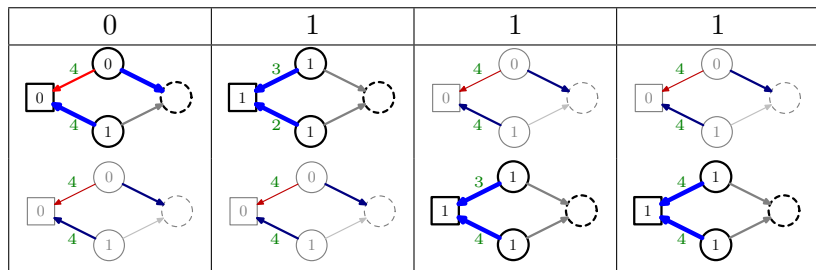
Only one representative subgadget is **active**. The **upper** representative is **active** iff the **next higher bit** is **not set**

Binary Counting with conjunctive representatives



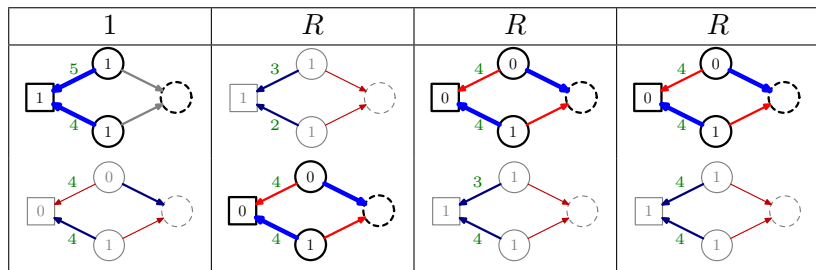
Only one representative subgadget is **active**. The **upper** representative is **active** iff the **next higher bit** is **not set**

Binary Counting with conjunctive representatives



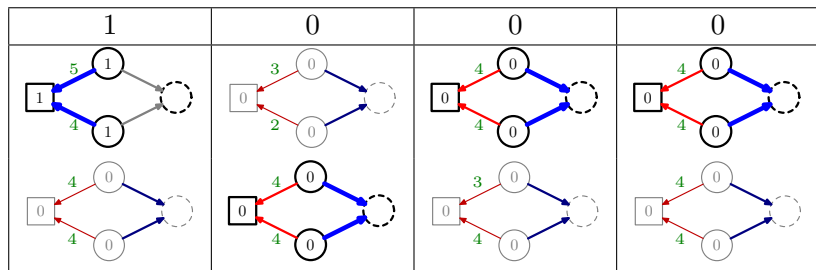
Only one representative subgadget is **active**. The **upper** representative is **active** iff the **next higher bit** is **not set**

Binary Counting with conjunctive representatives



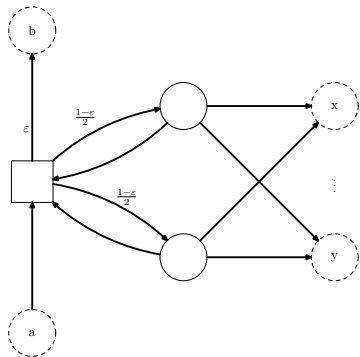
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Binary Counting with conjunctive representatives

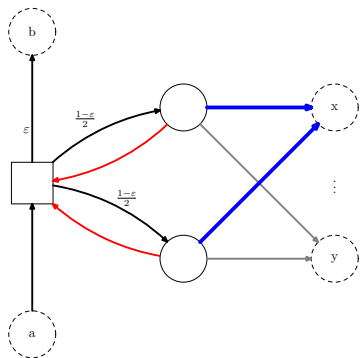


Only one representative subgadget is **active**. The **upper** representative is **active** iff the **next higher bit** is **not set**

Bit Gadget



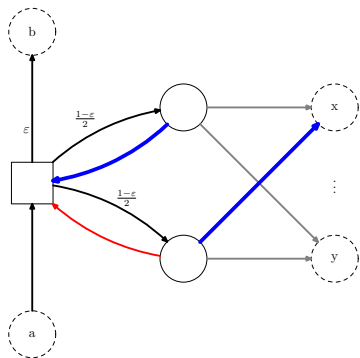
Bit Gadget



- Bit unset
- Improving to go in

$$\text{VAL}_\sigma(a) = \underbrace{\varepsilon \cdot \text{VAL}_\sigma(b)}_{\approx 0} + \underbrace{(1 - \varepsilon)}_{\approx 1} \cdot \text{VAL}_\sigma(x) \approx \text{VAL}_\sigma(x)$$

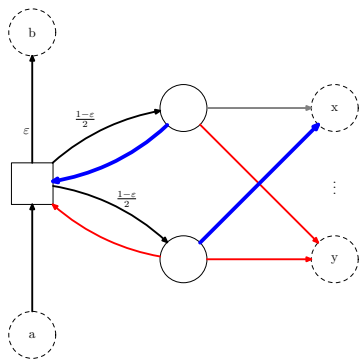
Bit Gadget



- Bit still unset (only one edge going in)
- Still improving to go in with the other edge

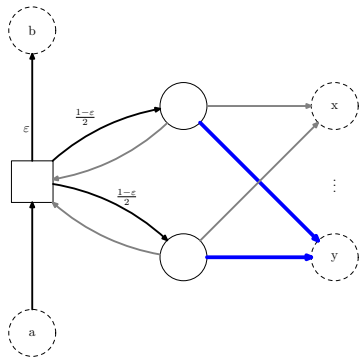
$$\text{VAL}_\sigma(a) = \underbrace{\frac{2\varepsilon}{1+\varepsilon} \cdot \text{VAL}_\sigma(b)}_{\approx 0} + \underbrace{\frac{1-\varepsilon}{1+\varepsilon} \cdot \text{VAL}_\sigma(x)}_{\approx 1} \approx \text{VAL}_\sigma(x)$$

Bit Gadget



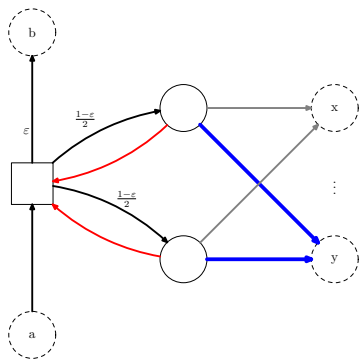
- y has now better valuation than x
- Gadget could close, but also open completely again

Bit Gadget



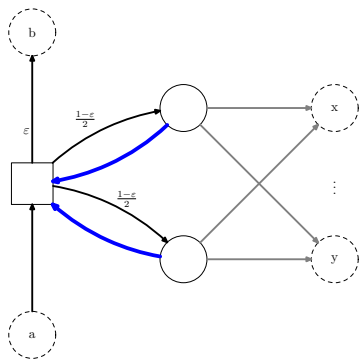
- Bit unset
- No improvements

Bit Gadget



- Bit unset
- Improving to go in

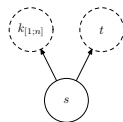
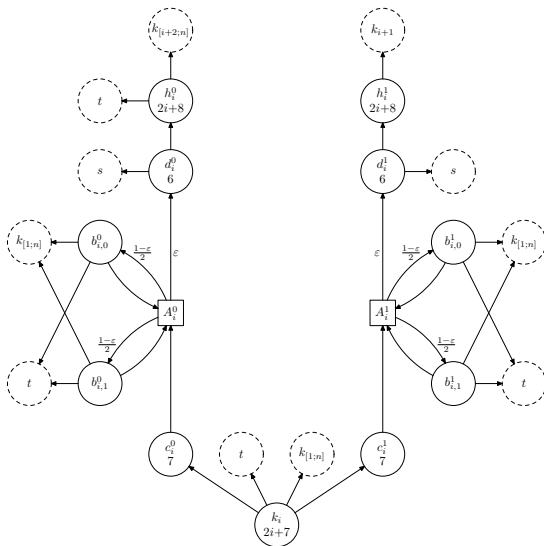
Bit Gadget



- Bit set
- Now b can be “observed” from a

$$\text{VAL}_\sigma(a) = \text{VAL}_\sigma(b)$$

Full Construction



Concluding Remarks

Open problems

- Obtain lower bounds for related history-based pivoting rules
 - Least-recently considered: subexponential lower bound
 - Least-recently basic, Least-recently entered, Least basic iterations: work in progress
- **Polytime** algorithm for two-player games and the like
- Strongly polytime algorithm for LPs (and MDPs)
- Resolving the **Hirsch conjecture**
- Find game-theoretic model with unresolved diameter bounds

The slide usually called “the end”.

Thank you for listening!