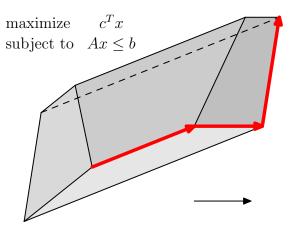
An exponential lower bound for Cunningham's rule

Oliver Friedmann

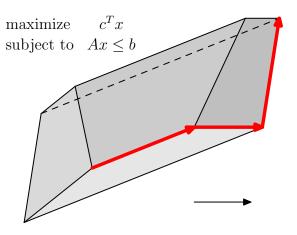
Revised March 20, 2015 (DA)

Linear Programming and Simplex

The simplex method, Dantzig (1947)

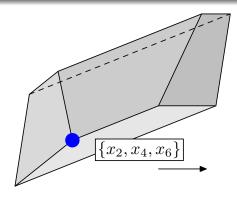


The simplex method, Dantzig (1947)



■ The first step is to add slack variables making a system of equations called a dictionary

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



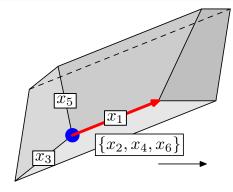
■ The vertices of the polytope are represented by basic feasible solutions formed by solving for 3 basic variables

$$\max \quad -1 + 2x_1 - 2x_3 - x_5$$
s.t.
$$x_2 = 1 - \frac{1}{3}x_1 + \frac{2}{3}x_3 + \frac{2}{3}x_5$$

$$x_4 = 2 - x_3 - x_5$$

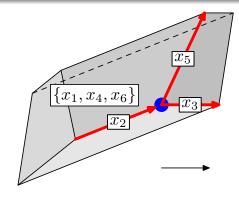
$$x_6 = 1 - x_5$$

$$x_1, x_2, x_3, x_4, x_5, x_6 \ge 0$$



- The vertices of the polytope are represented by basic feasible solutions formed by solving for 3 basic variables
- Moving along an edge corresponds to pivoting: exchange a basic variable(LHS) with a non-basic variable(RHS).

$$\begin{array}{lll} \max & 5-6x_2+2x_3+3x_5\\ \mathrm{s.t.} & x_1 &= 3-3x_2+2x_3+2x_5\\ & x_4 &= 2-x_3-x_5\\ & x_6 &= 1-x_5\\ & x_1,x_2,x_3,x_4,x_5,x_6 \geq 0 \end{array}$$



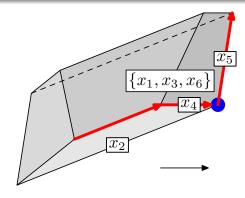
- The vertices of the polytope are represented by basic feasible solutions formed by solving for 3 basic variables
- Moving along an edge corresponds to pivoting: exchange a basic variable(LHS) with a non-basic variable(RHS).
- A non-basic variable with positive coefficient in the objective is chosen to enter the basis
- A pivot selection rule chooses which variable enters

$$\max \quad 9 - 6x_2 - 2x_4 + x_5$$
s.t.
$$x_1 = 7 - 3x_2 - 2x_4$$

$$x_3 = 2 - x_4 - x_5$$

$$x_6 = 1 - x_5$$

$$x_1, x_2, x_3, x_4, x_5, x_6 \ge 0$$



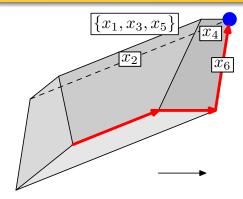
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$$\max 10 - 6x_2 - 2x_4 - x_6$$
s.t.
$$x_1 = 7 - 3x_2 - 2x_4$$

$$x_3 = 1 - x_4 + x_6$$

$$x_5 = 1 - x_6$$

$$x_1, x_2, x_3, x_4, x_5, x_6 \ge 0$$



- The vertices of the polytope are represented by basic feasible solutions formed by solving for 3 basic variables
- Moving along an edge corresponds to pivoting: exchange a basic variable(LHS) with a non-basic variable(RHS).
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Simplex and Pivots

A pivoting rule chooses the entering and leaving variable at each iteration

■ Deterministic, oblivious rules: eg. Largest coefficient (Dantzig), Least subscript (Bland), Greatest improvement are are known to be exponential.

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- We show an exponential lower bound for Cunningham's rule

Cunningham's ROUND-ROBIN rule

Order the variables cyclically in any way. Starting from the last entered variable, consider the vertices in circular order choosing the first candidate with positive objective coefficient.

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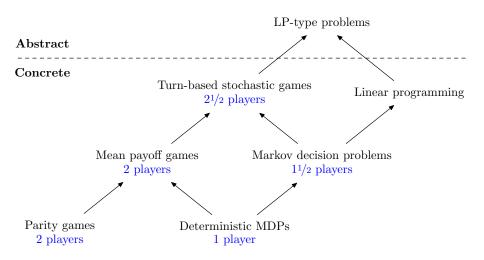
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Cunningham's ROUND-ROBIN rule

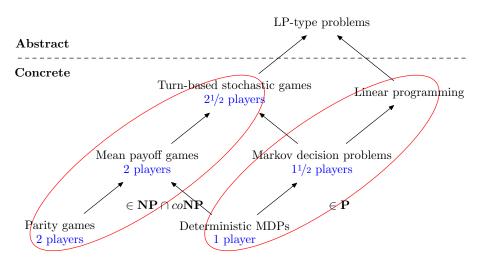
Order the variables cyclically in any way. Starting from the last entered variable, consider the vertices in circular order choosing the first candidate with positive objective coefficient.

- No analysis of history based rules for over 39 years
- They have some features in common with randomized rules (eg. fairness)
- Have some hope of being at least subexponential (?)

From Policy Iteration to Simplex

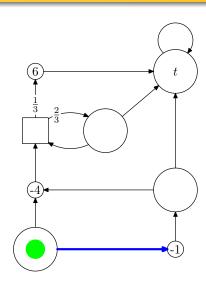


From Policy Iteration to Simplex

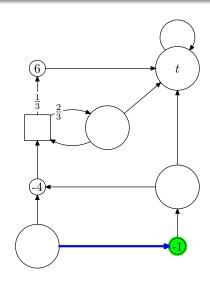


Games and Policy Iteration

- Large circle: player 0 (us)
- Square: player 1 (random)
- Small circle: our reward
- Edge: possible actions (with probability)
- Blue edge: action taken
- Green circle: current node
- Goal: maximize expected reward before reaching t from current node

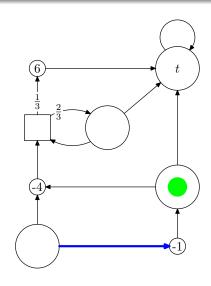


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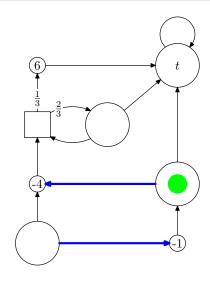
Reward: -1

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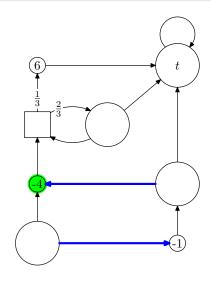
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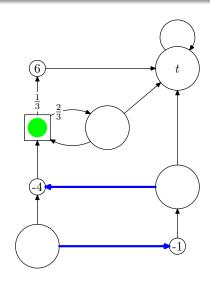
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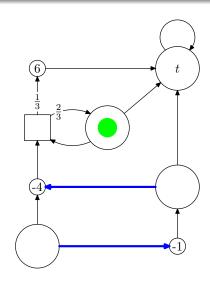
Reward: -1-4

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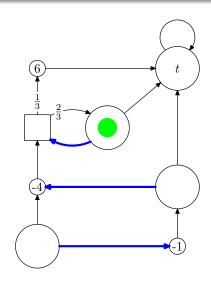
Reward: -1-4

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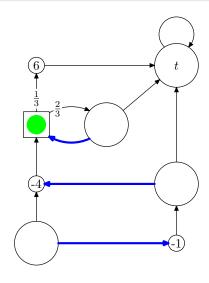
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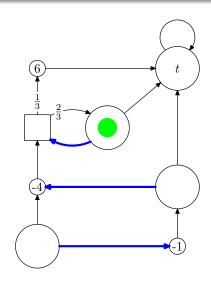
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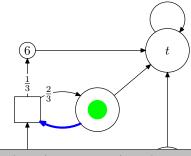
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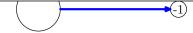
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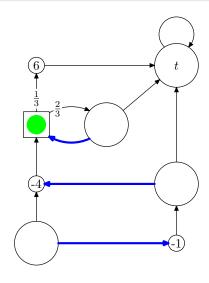
Shapley (1953), Bellman (1957):

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



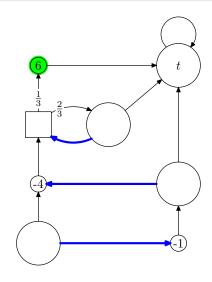
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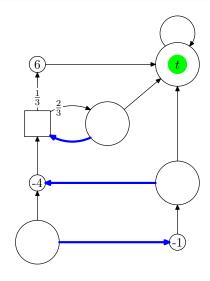
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Reward: -1 - 4 + 6

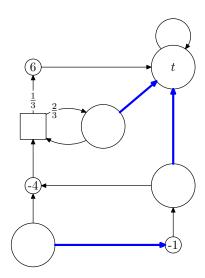
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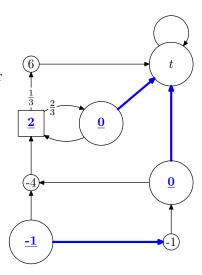
Reward: -1 - 4 + 6 = 1

Policies and corresponding values

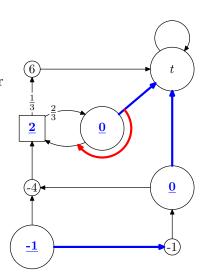
■ A policy π is a choice of an action each of our nodes. (blue edges)



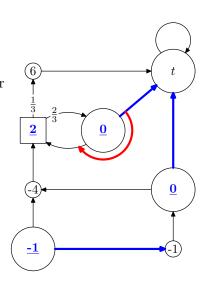
- A policy π is a choice of an action each of our nodes. (blue edges)
- The value $VAL_{\pi}(i)$ of a state $i \in S$ for a policy π , is the expected reward moving from i to t (blue numbers)



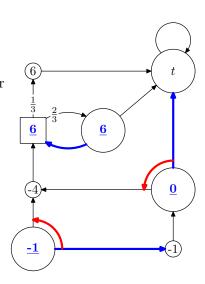
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- A policy change (pivot) is an improving switch w.r.t. π if it improves the value.



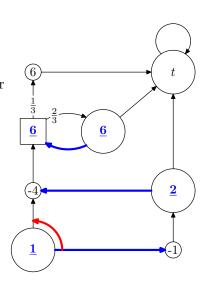
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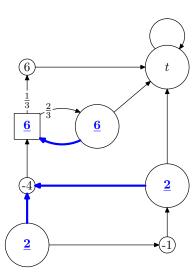
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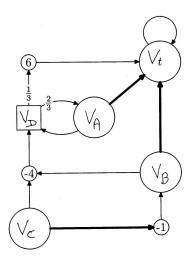
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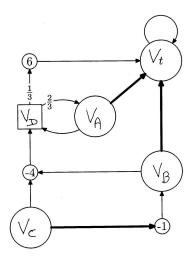
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- Policy improvement: make any improving switch
- A policy π^* is optimal iff there are no improving switches.



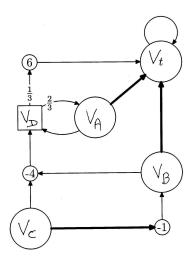
• Optimality conditions for each vertex: $v_i = VAL_{\pi}(i)$



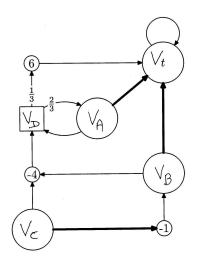
- Optimality conditions for each vertex: $v_i = VAL_{\pi}(i)$
- $v_A = \max\{v_D, v_t\}$



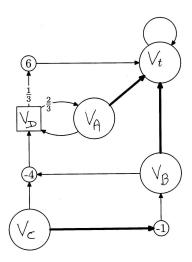
- Optimality conditions for each vertex: $v_i = VAL_{\pi}(i)$
- $v_A = \max\{v_D, v_t\}$
- $v_B = \max\{-4 + v_D, v_t\}$



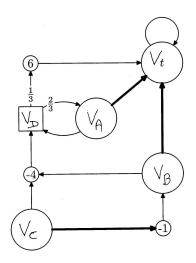
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- $v_B = \max\{-4 + v_D, v_t\}$
- $v_C = \max\{-4 + v_D, -1 + v_B\}$
- $v_D = \frac{1}{3}(6+v_t) + \frac{2}{3}v_A$

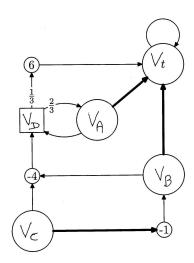


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- $v_D = \frac{1}{3}(6+v_t) + \frac{2}{3}v_A$
- Note: $v_t = 0$



lacktriangle Optimality conditions

$$\begin{array}{rcl} v_A & = & \max\{v_D, 0\} \\ v_B & = & \max\{-4 + v_D, 0\} \\ v_C & = & \max\{-4 + v_D, -1 + v_B\} \\ v_D & = & 2 + \frac{2}{3}v_A \end{array}$$

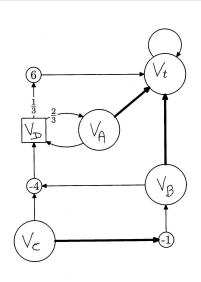


Optimality conditions

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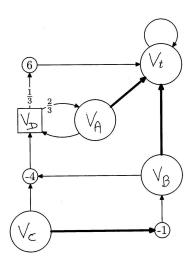
■ Linear Program

$$\begin{aligned}
\min w &= v_A + v_B + v_C \\
v_A &\geq v_D \\
v_A &\geq 0 \\
v_B &\geq -4 + v_D \\
v_B &\geq 0 \\
v_C &\geq -4 + v_D \\
v_C &\geq -1 + v_B \\
v_D &= 2 + \frac{2}{3}v_A
\end{aligned}$$



■ Optimality conditions

$$\begin{array}{rcl} v_A & = & \max\{v_D, 0\} \\ v_B & = & \max\{-4 + v_D, 0\} \\ v_C & = & \max\{-4 + v_D, -1 + v_B\} \\ v_D & = & 2 + \frac{2}{3}v_A \end{array}$$



Optimality conditions

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■ Linear Program (v_D eliminated)

$$\min w = v_A + v_B + v_C$$

$$v_A \ge 2 + \frac{2}{3}v_A$$

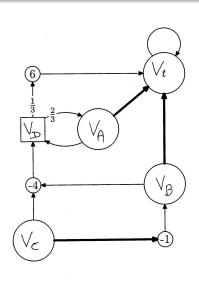
$$v_A \ge 0$$

$$v_B \ge -2 + \frac{2}{3}v_A$$

$$v_B \ge 0$$

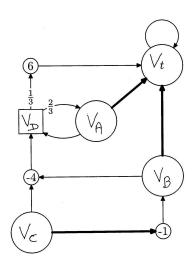
$$v_C \ge -2 + \frac{2}{3}v_A$$

$$v_C \ge -1 + v_B$$



Optimality conditions

$$\begin{array}{rcl} v_A & = & \max\{v_D, 0\} \\ v_B & = & \max\{-4 + v_D, 0\} \\ v_C & = & \max\{-4 + v_D, -1 + v_B\} \\ v_D & = & 2 + \frac{2}{3}v_A \end{array}$$

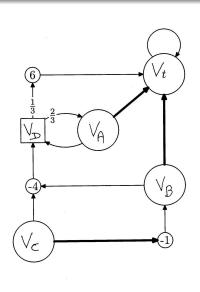


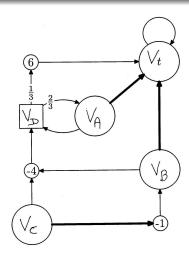
■ Optimality conditions

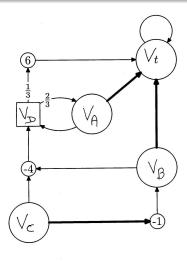
$$\begin{array}{rcl} v_A & = & \max\{v_D, 0\} \\ v_B & = & \max\{-4 + v_D, 0\} \\ v_C & = & \max\{-4 + v_D, -1 + v_B\} \\ v_D & = & 2 + \frac{2}{3}v_A \end{array}$$

■ Linear Program (Dual standard form)

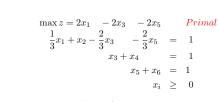
$$\min w = v_A + v_B + v_C
 \frac{1}{3}v_A & \geq 2
 v_A & \geq 0
 -\frac{2}{3}v_A + v_B & \geq -2
 v_B & \geq 0
 -\frac{2}{3}v_A & +v_C & \geq -2
 -v_B + v_C & \geq -1$$

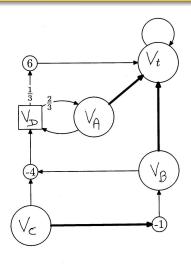






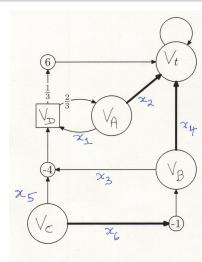
$$\max z = 2x_1 - 2x_3 - 2x_5 \qquad \begin{array}{lll} & Primal \\ \frac{1}{3}x_1 + x_2 - \frac{2}{3}x_3 & -\frac{2}{3}x_5 & = & 1 \\ & & x_3 + x_4 & = & 1 \\ & & & x_5 + x_6 & = & 1 \\ & & & & x_5 & \geq & 0 \end{array}$$



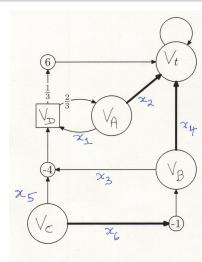


■ What are the variables x_i ?

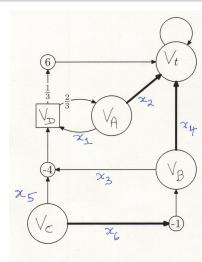
■ The x_i are action variables!



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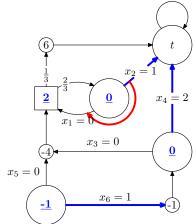


■ The x_i are action variables!



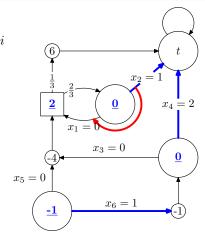
Variables of the primal LP

• x_i is the expected number of times action i is used, summed over all starting states.



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- The actions taken form the basic variables of the LP



Variables of the primal LP

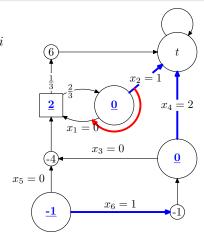
- x_i is the expected number of times action i is used, summed over all starting states.
- The actions taken form the basic variables of the LP
- Solving for $\{x_2, x_4, x_6\}$ we get:

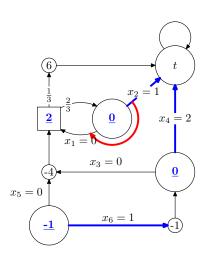
$$\max -1 + 2x_1 - 2x_3 - x_5$$
s.t.
$$x_2 = 1 - \frac{1}{3}x_1 + \frac{2}{3}x_3 + \frac{2}{3}x_5$$

$$x_4 = 2 - x_3 - x_5$$

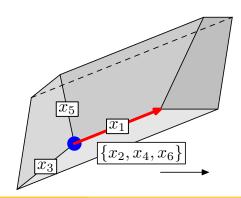
$$x_6 = 1 - x_5$$

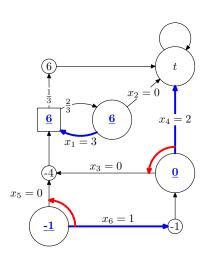
$$x_1, x_2, x_3, x_4, x_5, x_6 \ge 0$$





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



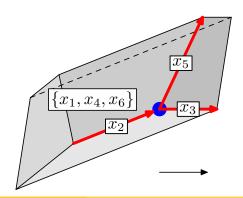


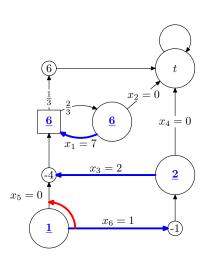
$$\max \quad 5 - 6x_2 + 2x_3 + 3x_5$$
s.t.
$$x_1 = 3 - 3x_2 + 2x_3 + 2x_5$$

$$x_4 = 2 - x_3 - x_5$$

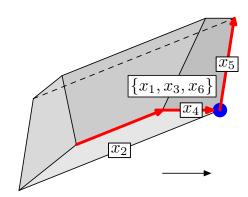
$$x_6 = 1 - x_5$$

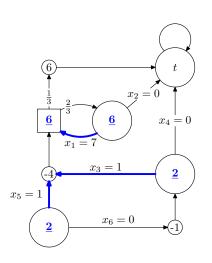
$$x_1, x_2, x_3, x_4, x_5, x_6 \ge 0$$



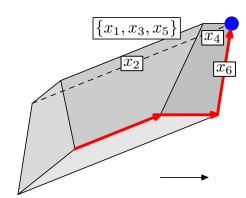


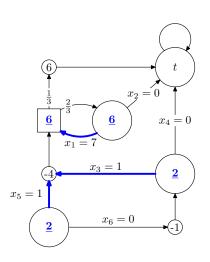
$$\begin{array}{lll} \max & 9-6x_2-2x_4+x_5\\ \text{s.t.} & x_1 &= 7-3x_2-2x_4\\ & x_3 &= 2-x_4-x_5\\ & x_6 &= 1-x_5\\ & x_1,x_2,x_3,x_4,x_5,x_6 \geq 0 \end{array}$$



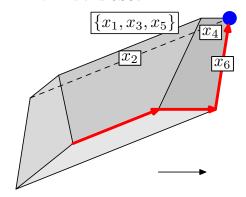


$$\begin{array}{lll} \max & 10-6x_2-2x_4-x_6\\ \text{s.t.} & x_1 &= 7-3x_2-2x_4\\ & x_3 &= 1-x_4+x_6\\ & x_5 &= 1-x_6\\ & x_1,x_2,x_3,x_4,x_5,x_6 \geq 0 \end{array}$$





- \blacksquare Out degree of player 0 nodes = 2
- Polyhedron is a deformed cube
- Oriented by objective function polyhedron gives an acyclic USO
- Degree 2 MDPs give lower bounds for LPs and USOs!



Optimality Theorem for MDP and LP

• Optimal policy π^* :

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

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

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

■ LP formulation:

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

Primal and dual LPs for MDPs

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

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

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

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

$$x_a \ge 0, \quad \forall a$$

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 policy improvement algorithm ≡ simplex method on primal

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

$$x_a > 0, \forall a$$

- policy improvement algorithm ≡ simplex method on primal
- Finiteness and correctness of policy improvement follow from finiteness and correctness of simplex method

Primal and dual LPs for MDPs

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

s.t.
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$$\text{maximize} \quad \sum_{i \in S} \sum_{a \in A_i} r_a x_a$$

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

$$x_a > 0, \forall a$$

- policy improvement algorithm ≡ simplex method on primal
- Finiteness and correctness of policy improvement follow from finiteness and correctness of simplex method
- Lower bounds for policy improvement give lower bounds for simplex method!

Lower Bound for Least Recently Considered Rule

Lower bound construction

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

Lower bound construction

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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 ROUND-ROBIN 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.

$$\cdots < 5 < 3 < 1 < 2 < 4 < 6 < \cdots$$
for
$$(-N)^5$$

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

Selection Ordering

Cunningham's ROUND-ROBIN rule

Perform improving switches in a round-robin fashion.

Selection Ordering = linear ordering on the edges

Proof of Small Diameter Theorem implies:

Corollary

There is a selection ordering s.t. Cunningham's rule requires linearly many iterations in the worst-case.

Consequence: lower bound construction is equipped with particular selection ordering

24

■ Simulate binary counter

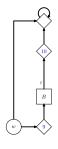


- Simulate binary counter
- End in a single sink loop with no cost

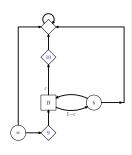


- Simulate binary counter
- End in a single sink loop with no cost
- Incrementation of binary counter consists of intermediate phases

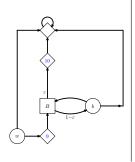




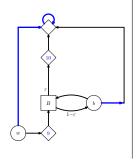
- Simulate binary counter
- End in a single sink loop with no cost
- Incrementation of binary counter consists of intermediate phases
- Structure relating to single bit as profitable pass-through structure if bit is set



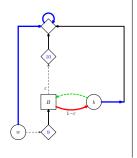
- Simulate binary counter
- End in a single sink loop with no cost
- Incrementation of binary counter consists of intermediate phases
- Structure relating to single bit as profitable pass-through structure if bit is set
- Implementation of bit structure by zero-cost cycles with exponentially small exit-probability



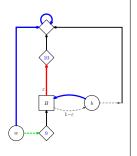
■ Choose starting policy



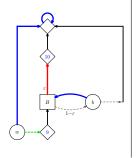
- Choose starting policy
- $v_w = 0, v_b = 0$ b unset



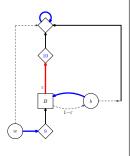
- Choose starting policy
- $v_w = 0, v_b = 0$ b unset
- Improving switch found



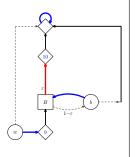
- Choose starting policy
- $v_w = 0, v_b = 0$ b unset
- Improving switch found
- $v_w = 0, v_b = r_{10} > 0$



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- $v_w = 0, v_b = 0$ b unset
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- Improving switch found

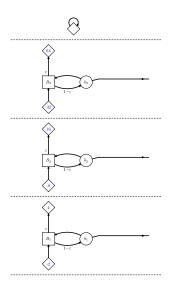


- Choose starting policy
- $v_w = 0, v_b = 0$ b unset
- Improving switch found
- $v_w = 0, v_b = r_{10} > 0$
- Improving switch found
- $v_w = r_9 + r_{10} > 0, v_b = r_{10} > 0$ b set



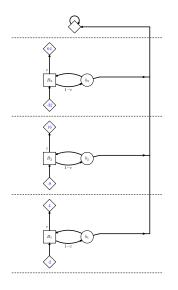
- Choose starting policy
- $v_w = 0, v_b = 0$ b unset
- Improving switch found
- $v_w = 0, v_b = r_{10} > 0$
- Improving switch found
- $v_w = r_9 + r_{10} > 0, v_b = r_{10} > 0$ b set
- No improving switches for any valid choice of r_9 , r_{10}

| <u>\tag{\text{\tint{\text{\tin}\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\tex{\tex</u> | |
|--|--------------------------------|
| | Start with a single sink node. |
| | |
| | |

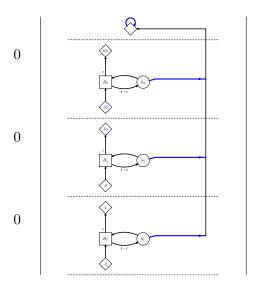


Add three bits. Design principles:

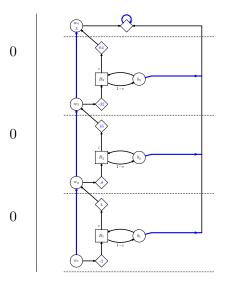
- Every bit is represented by a simple cycle.
- Going through a set bit is profitable.
- Going through an unset bit is unprofitable.
- Going through higher set bits is more profitable than going through lower set bits.



Connect all bits with the sink.

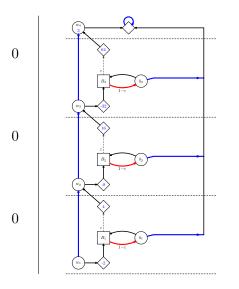


Start with unset bits.

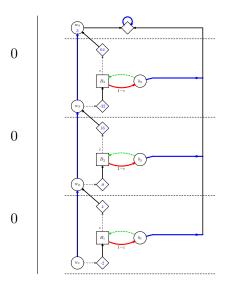


Add uplink structure that allows to go through set bits or bypass them.

$$v_i = 0$$
 for all i



Small exit-probability almost hides the value of the exit nodes completely.



It is improving to set any of the bits.

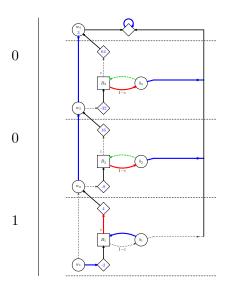
This will be a general principle: All unset bits can be set at the same time.

0 0

First bit has been set.

$$z = 4$$
$$v_{b_1} = 4$$

- The exit node will be eventually taken with probability 1.
- It is now profitable to go through the set bit.



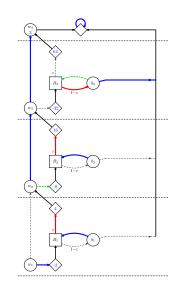
Update uplink of first bit: go through.

$$z = 6 v_{w_1} = 2, v_{b_1} = 4$$

0

1

1



Second bit has been set.

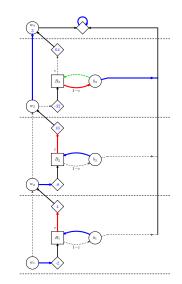
$$z = 22$$

$$v_{w_1} = 2, v_{b_1} = 4, v_{b_2} = 16$$

0

1

1



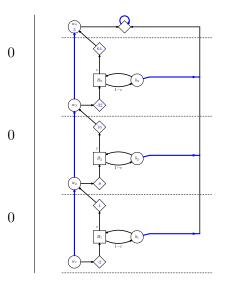
Update uplink of second bit: go through.

$$z = 46$$

$$v_{w_1} = 10, v_{b_1} = 12$$

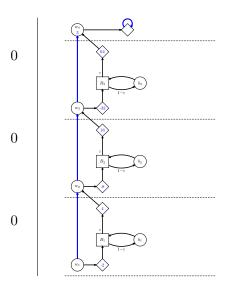
$$v_{w_2} = 8, v_{b_2} = 16$$

Problem: we cannot reuse the first bit again.

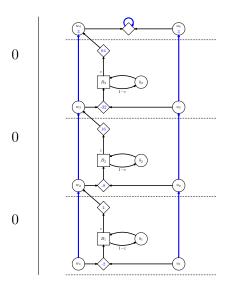


Start over again.

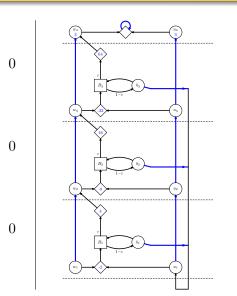
- Setting a higher bit has to lead to resetting the lower bits.
- There have to be outgoing edges of the cycles that have immediate access to the next set bit.



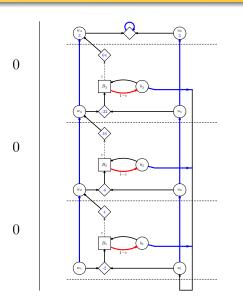
Remove direct link to the sink.



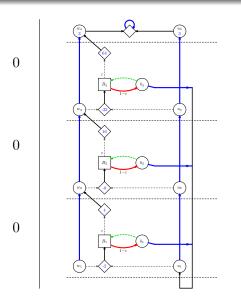
Add second uplink structure, called selector structure.



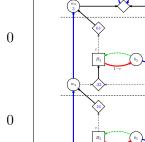
Give all cycles immediate access to the selector structure.



Small exit-probability still hides the value of the exit nodes completely.

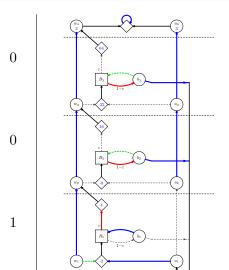


It is still improving to set any of the bits.



Step 1: First bit has been set.

$$z = 4$$
$$v_{b_1} = 4$$



Step 2: Update selector of first bit.

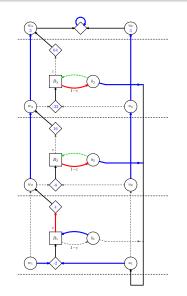
$$z = 10$$

$$v_{b_2} = v_{b_3} = v_{u_1} = 2, v_{b_1} = 4$$

0

0

1



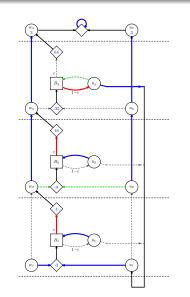
Step 4: Update uplink of first bit. (Step 3 missing)

$$\begin{aligned}
 z &= 12 \\
 v_{w_1} &= v_{b_2} = v_{b_3} = v_{u_1} = 2 \\
 v_{b_1} &= 4
 \end{aligned}$$

0

1

 \mathbf{R}



Step 1: Second bit has been set.

$$z = 26$$

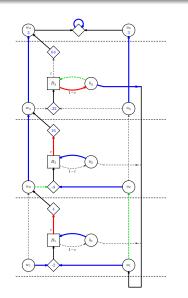
$$v_{w_1} = v_{b_3} = v_{u_1} = 2$$

$$v_{b_1} = 4, v_{b_2} = 16$$

0

1

 \mathbf{R}



Step 2: Update selector of second bit.

$$z = 34$$

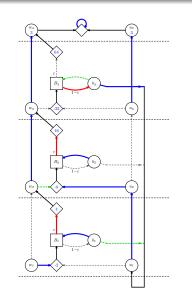
$$v_{w_1} = v_{b_3} = v_{u_1} = 2$$

$$v_{b_1} = 4, v_{b_2} = 16, v_{u_2} = 8$$

0

1

 \mathbf{R}



Step 2: Update selector of first bit.

$$z = 46$$

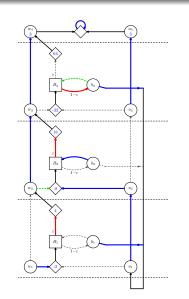
$$v_{b_3} = v_{u_1} = v_{u_2} = 8$$

$$v_{b_1} = 4, v_{b_2} = 16, v_{w_1} = 2$$

0

1

0



Step 3: Reset first bit.

$$z = 54 - 4\epsilon$$

$$v_{b_1} = v_{b_3} = v_{u_1} = v_{u_2} = 8$$

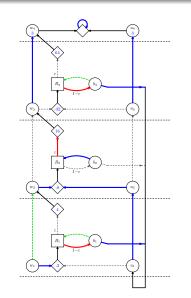
$$v_{b_2} = 16$$

$$v_{w_1} = -2 + 4\epsilon + 8(1 - \epsilon) = 6 - 4\epsilon$$

0

1

0



Step 4: Update uplink of second bit.

$$z = 62 + 4\epsilon$$

$$v_{b_1} = v_{b_3} = v_{u_1} = v_{u_2} = 8$$

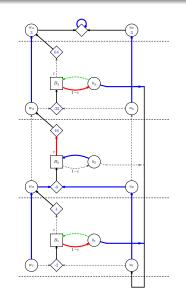
$$v_{b_2} = 16, v_{w_2} = 8$$

$$v_{w_1} = -2 + 12\epsilon + 8(1 - \epsilon) = 6 + 4\epsilon$$



1

0



Step 4: Update uplink of first bit.

$$z = 64$$

(Setting
$$\epsilon = 1/4, 62 + 4\epsilon < 64$$
)

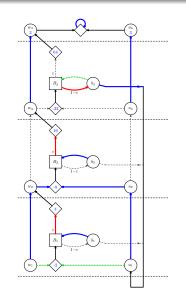
$$v_{b_1} = v_{b_3} = v_{u_1} = v_{u_2} = 8$$

 $v_{b_2} = 16, v_{w_1} = v_{w_2} = 8$

0

1

1



Step 1: First bit has been set.

$$z = 68$$

$$v_{b_1} = 12, v_{b_3} = v_{u_1} = v_{u_2} = 8$$

$$v_{b_2} = 16, v_{w_1} = v_{w_2} = 8$$

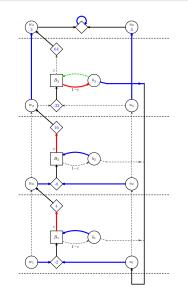
Step 2: Update selector of first bit.

$$\begin{split} z &= 72 \\ v_{b_1} &= 12, v_{b_3} = v_{u_1} = 10 \\ v_{b_2} &= 16, v_{u_2} = v_{w_1} = v_{w_2} = 8 \end{split}$$

0

1

1



Step 4: Update uplink of first bit. (Step 3 missing)

$$z = 74$$

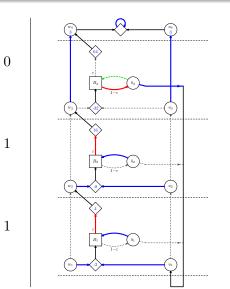
$$v_{b_1} = 12, v_{w_1} = v_{b_3} = v_{u_1} = 10$$

$$v_{b_2} = 16, v_{u_2} = v_{w_2} = 8$$

0

Intermediate Steps:

- I Set least unset bit by moving into cycle.
- 2 Update selector lane.
- Reset lower set bits by using selector lane.
- 4 Update uplink lane.



Summary:

- Generalizes to give *n*-bit binary counter
- 2 Exponential number of policy improvements
- Corresponding LP has exponential number of pivots
- 4 Tune for particular pivot selection rule

We now give a lower bound on:

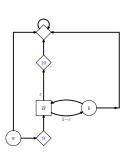
Least Recently Considered

Select improving edge in a round robin fashion.

An ordering on the edges is fixed.

Theorem: there is an ordering on the edges s.t. the Round Robin Rule solves the game in linearly many iterations.

Hence: we, as designers, specify the ordering



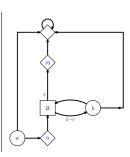
We now give a lower bound on:

Least Recently Considered

Select improving edge in a round robin fashion.

Ordering: order edges s.t. steps 1–4 are performed one after the other

Problem: all unset bits can be set at the same time.



We now give a lower bound on:

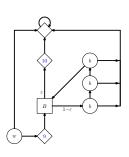
Least Recently Considered

Select improving edge in a round robin fashion.

Ordering: order edges s.t. steps 1–4 are performed one after the other

Problem: all unset bits can be set at the same time.

Solution: replace simple cycles of higher bits by longer cycles

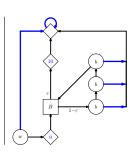


We now give a lower bound on:

Least Recently Considered

Select improving edge in a round robin fashion.

Start with unset bit again.

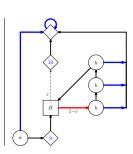


We now give a lower bound on:

Least Recently Considered

Select improving edge in a round robin fashion.

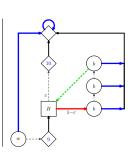
Start with unset bit again.



We now give a lower bound on:

Least Recently Considered

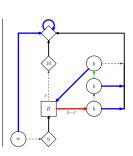
Select improving edge in a round robin fashion.



We now give a lower bound on:

Least Recently Considered

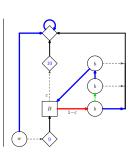
Select improving edge in a round robin fashion.



We now give a lower bound on:

Least Recently Considered

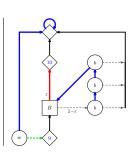
Select improving edge in a round robin fashion.



We now give a lower bound on:

Least Recently Considered

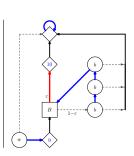
Select improving edge in a round robin fashion.

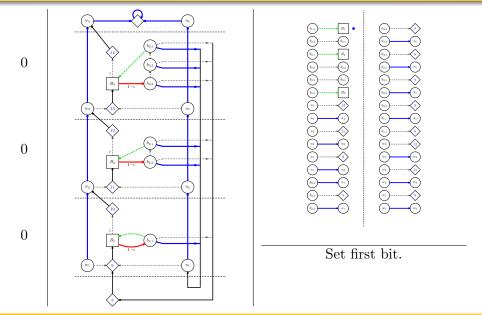


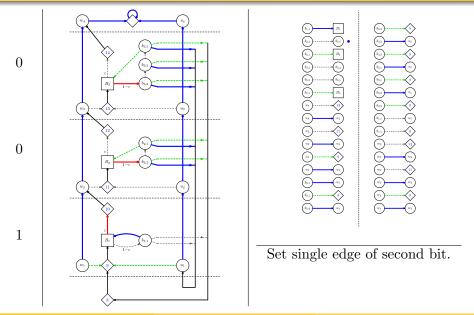
We now give a lower bound on:

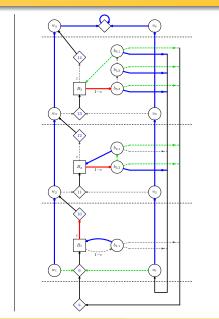
Least Recently Considered

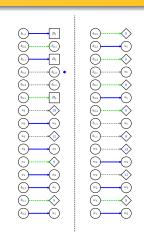
Select improving edge in a round robin fashion.







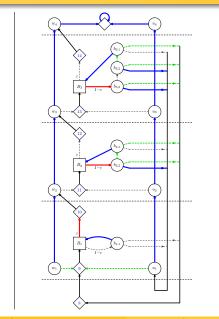


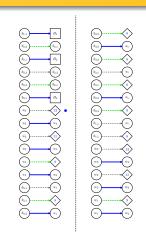


Other edge of second bit now improving, but smaller. Set single edge of third bit.

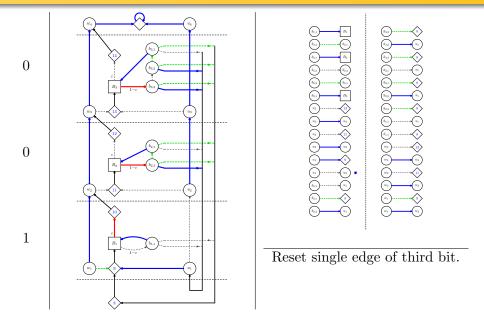
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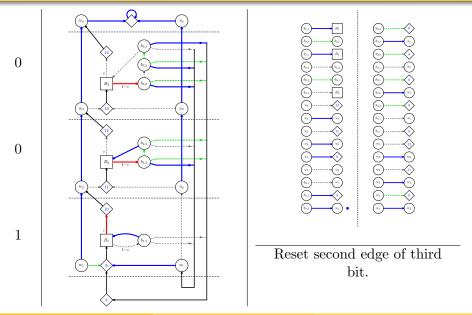
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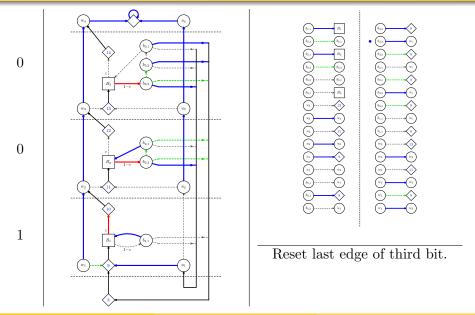


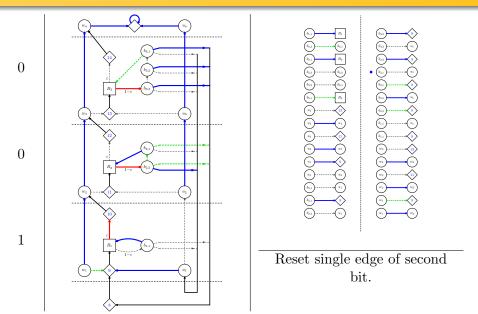


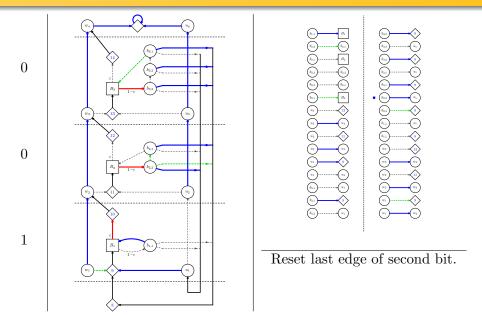
Second edge of third bit now improving, but smaller.
Update selector of first bit.

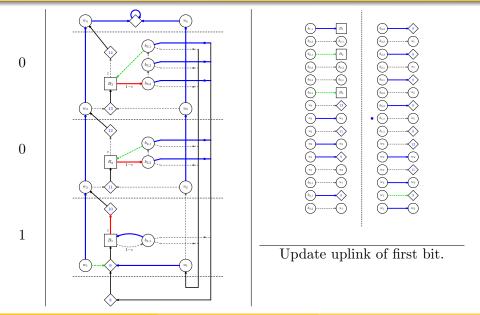


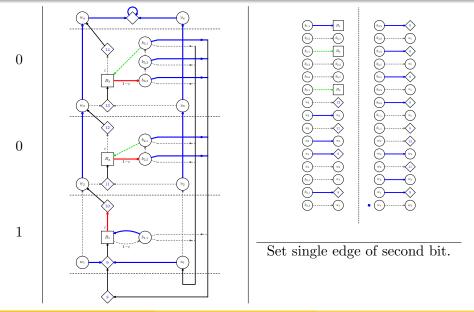


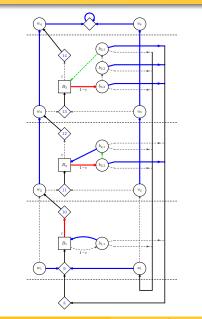


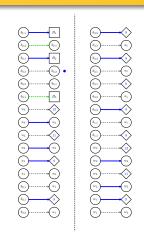








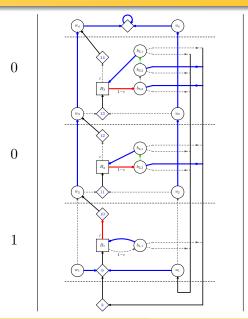


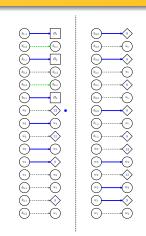


Other edge of second bit now improving, but smaller. Set single edge of third bit.

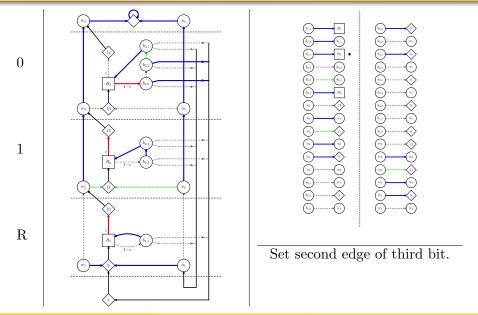
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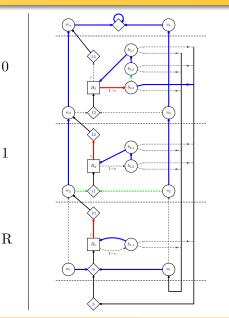
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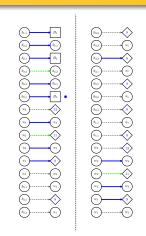




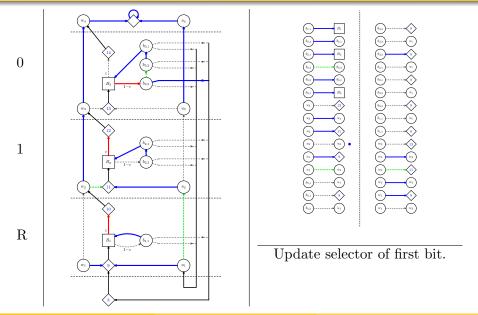
Set other edge of second bit, i.e. set second bit.

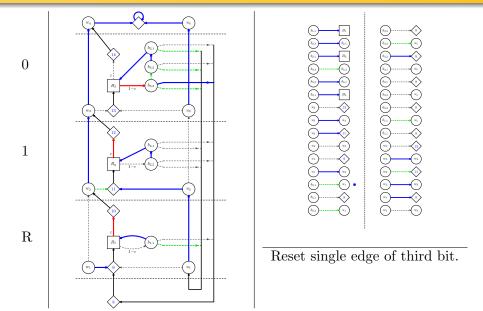


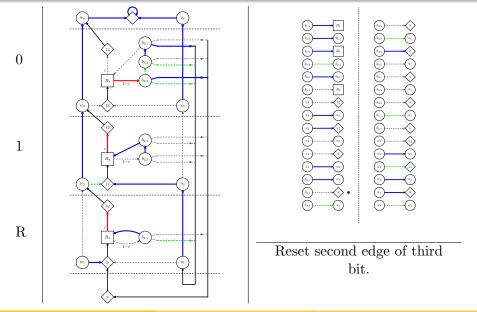


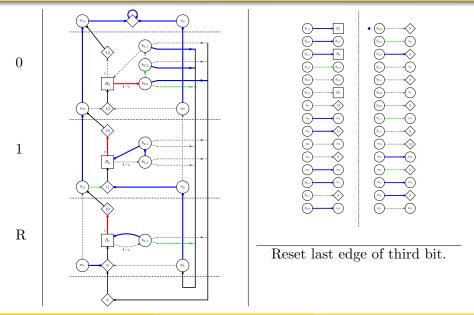


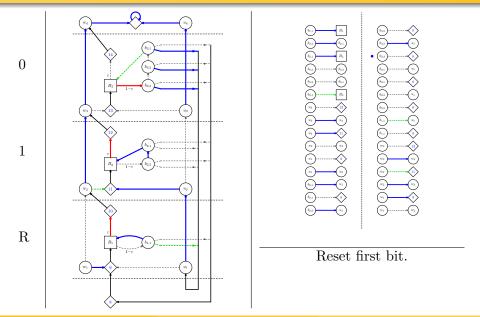
Last edge of third bit now improving, but smaller.
Update selector of second bit.

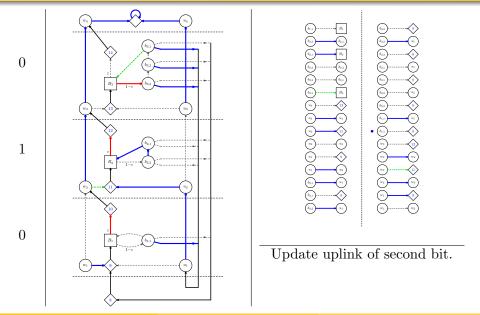


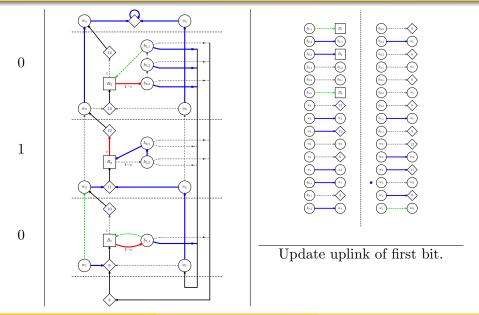


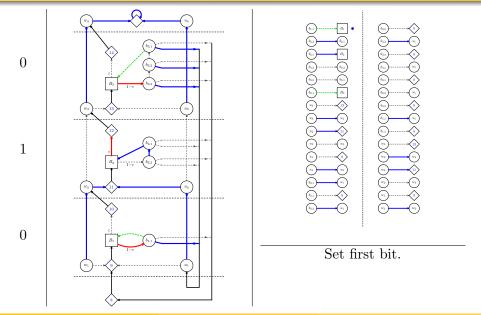


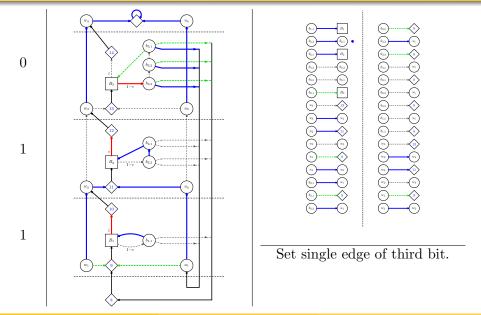


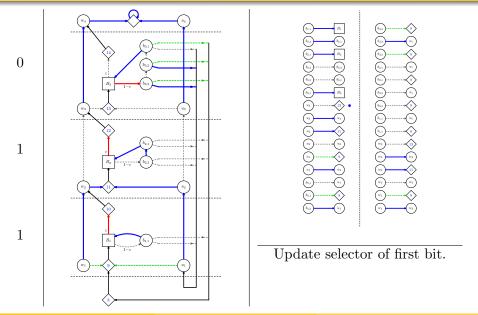


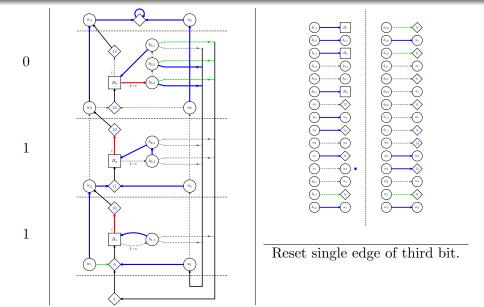


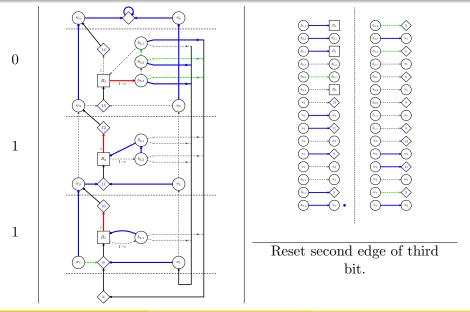


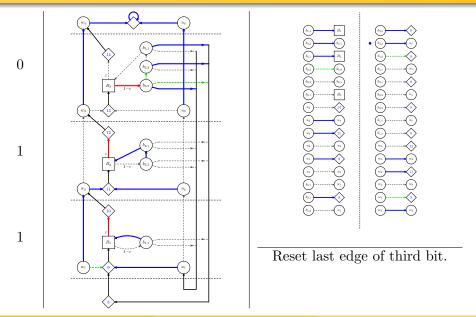


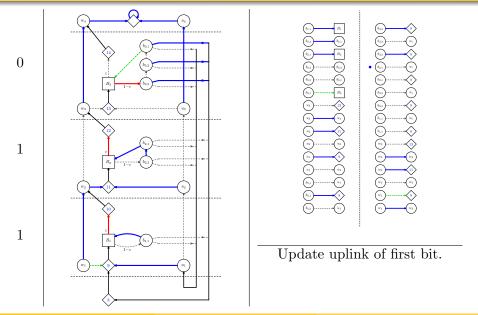


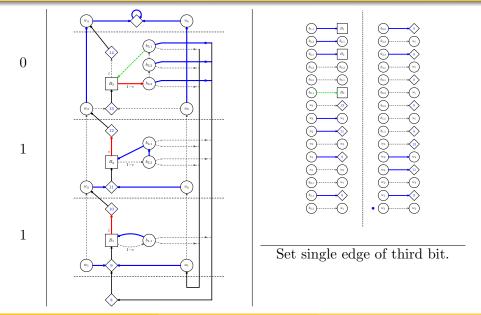


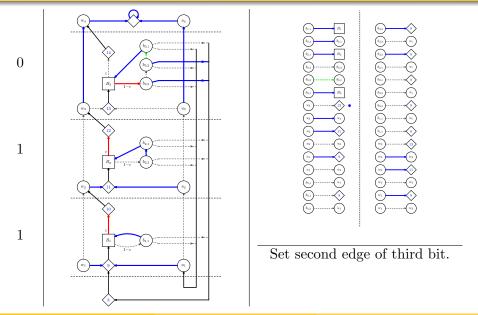


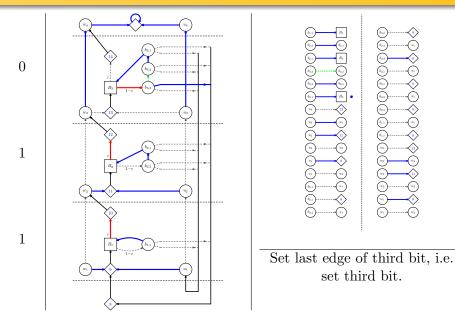


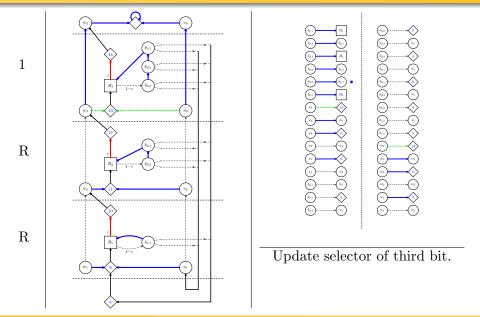


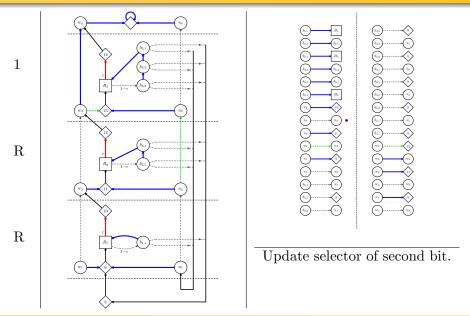


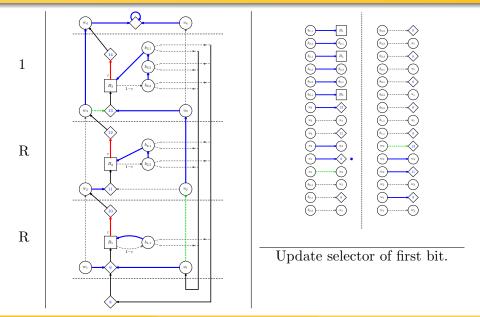


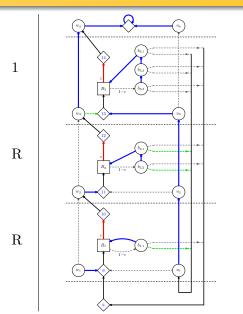


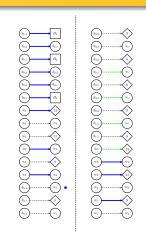




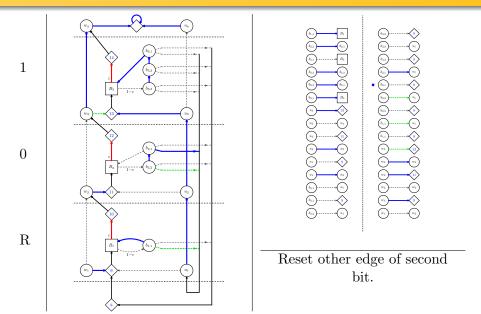


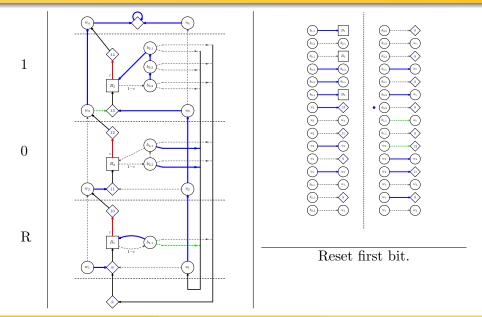


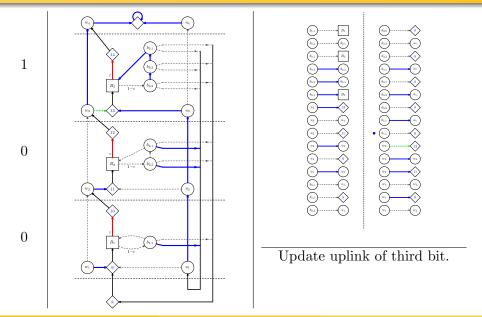


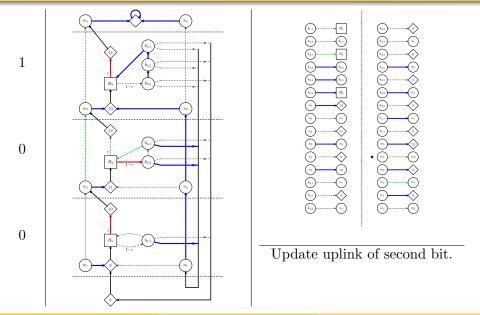


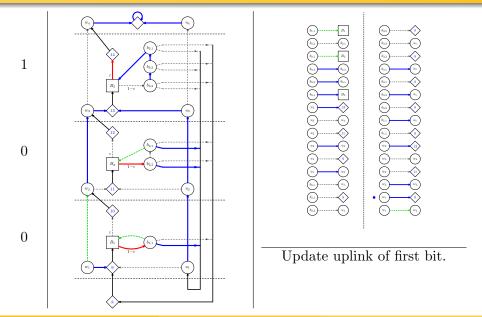
Reset first edge of second bit, i.e. reset second bit.

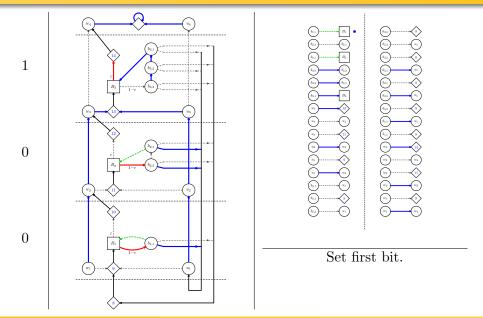


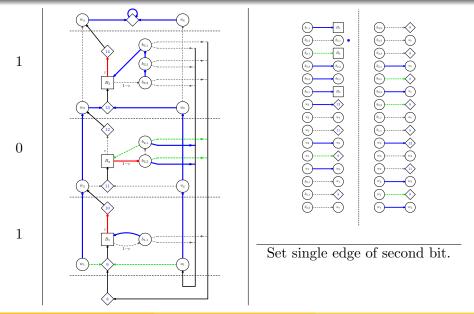


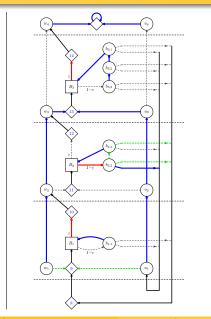


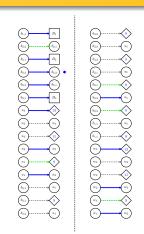




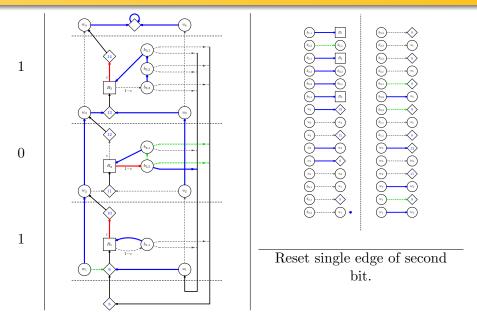


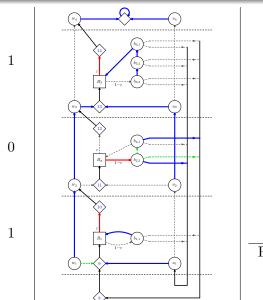


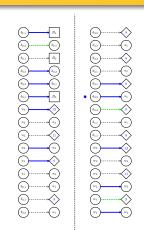




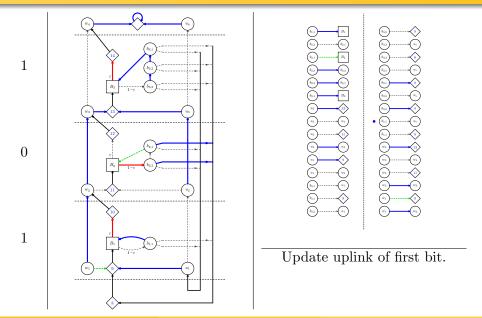
Other edge of second bit now improving, but smaller.
Update selector of first bit.

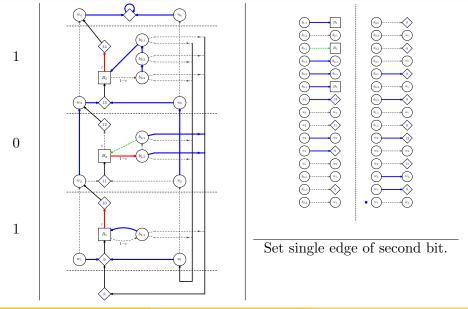


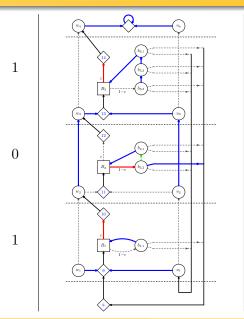


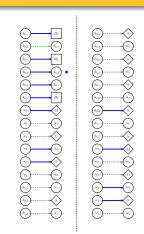


Reset last edge of second bit.

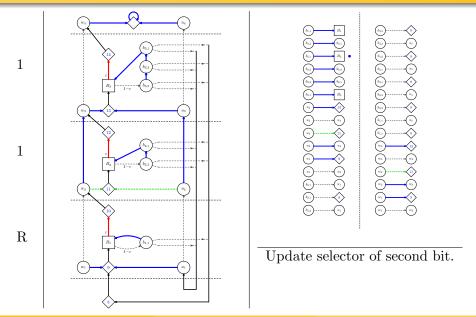


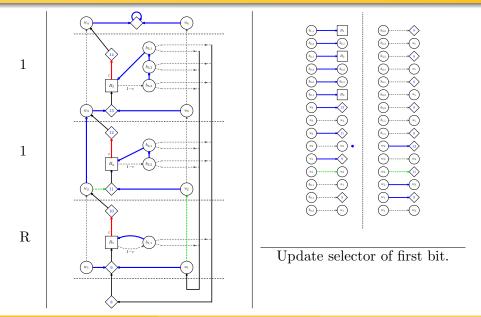


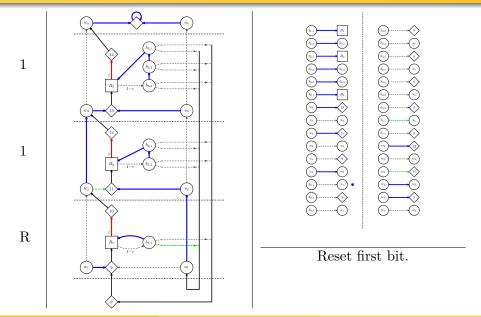


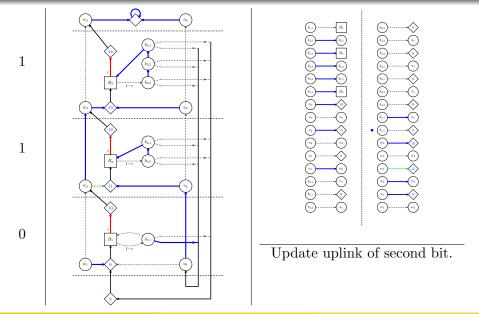


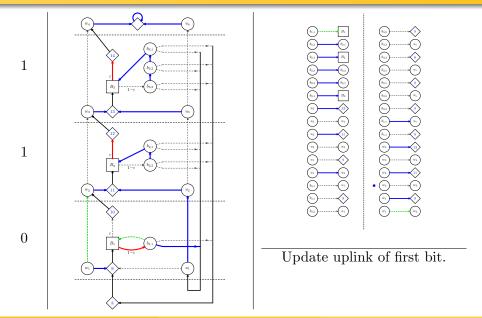
Set other edge of second bit, i.e. set second bit.

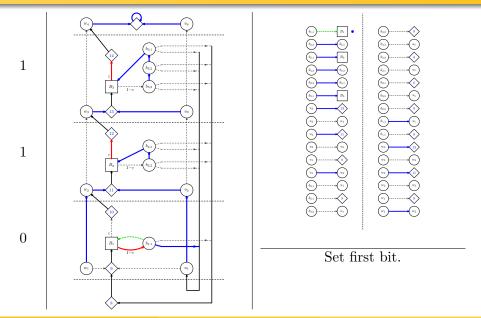


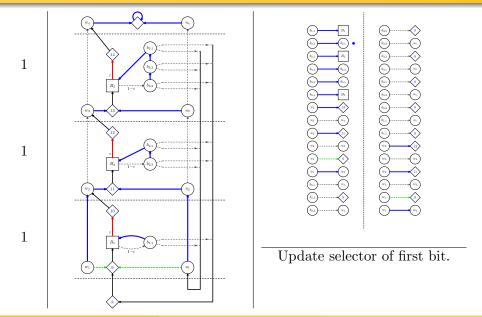


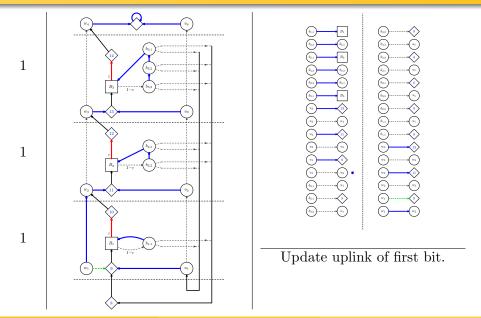


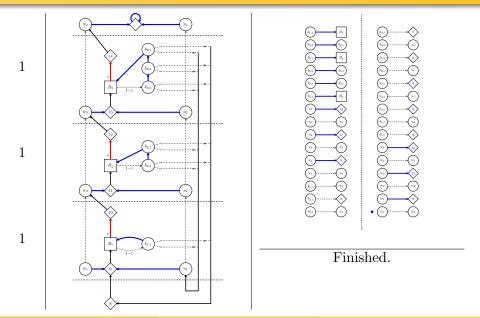


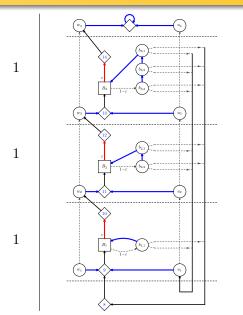


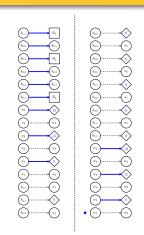




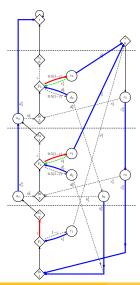




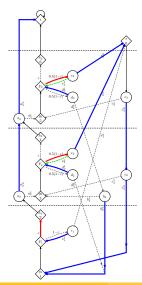




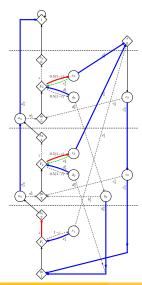
Subexponential lower bound Some out degrees are 3



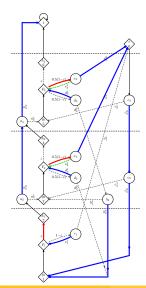
■ Lower bound is exponential in MDP size



- Lower bound is exponential in MDP size
- Binary node-out-degree



- Lower bound is exponential in MDP size
- Binary node-out-degree
- Applies to LP and acyclic USO



- Lower bound is exponential in MDP size
- Binary node-out-degree
- Applies to LP and acyclic USO
- Paper and animation available at www.oliverfriedmann.com

Corresponding LP

(LHS variables show binary node-out-degree)

$$\begin{array}{ll} \max & \sum_{i=1}^{n} \left(\left(a_{i}^{1} + b_{i}^{1} + c_{i}^{1} \right) \cdot \left(\Omega(g_{i}) + \varepsilon \cdot \Omega(h_{i}) \right) + \left(d_{i}^{1} + e_{i}^{1} \right) \cdot \varepsilon \cdot \Omega(h_{i}) + e_{i}^{0} \cdot \Omega(s) \right) \\ \mathrm{s.t.} & (a_{i}) & a_{i}^{1} + a_{i}^{0} = 1 + a_{i-1}^{0} + \varepsilon \cdot \left(a_{i-1} + b_{i-1} + c_{i-1} + d_{i-1} + e_{i-1} \right) \\ & (b_{i}) & b_{i}^{1} + b_{i}^{0} = 1 + b_{i+1}^{0} + d_{i+1}^{0} \\ & (c_{i}) & c_{i}^{1} + c_{i}^{0} = 1 + \begin{cases} c_{i+1}^{0} & \text{if } i < n \\ \sum_{j=1}^{n} e_{j}^{0} & \text{if } i = n \end{cases} \\ & (d_{i}) & d_{i}^{1} + d_{i}^{0} = 1 + \left(a_{i}^{1} + b_{i}^{1} + c_{i}^{1} + d_{i}^{1} + e_{i}^{1} \right) \cdot \begin{cases} \frac{1-\varepsilon}{2} & \text{if } i > 1 \\ 1-\varepsilon & \text{if } i = 1 \end{cases} \\ & (e_{i}) & e_{i}^{1} + e_{i}^{0} = 1 + \left(a_{i}^{1} + b_{i}^{1} + c_{i}^{1} + d_{i}^{1} + e_{i}^{1} \right) \cdot \begin{cases} \frac{1-\varepsilon}{2} & \text{if } i > 1 \\ 1-\varepsilon & \text{if } i = 1 \end{cases} \end{array}$$

Concluding Remarks

Open problems

- Obtain lower bounds for related history-based pivoting rules
 - Least-recently basic
 - Least-recently entered
 - Least basic iterations

Open problems

- Obtain lower bounds for related history-based pivoting rules
 - Least-recently basic
 - Least-recently entered
 - Least basic iterations
- Get lower bounds for the Network simplex method

Open problems

- Obtain lower bounds for related history-based pivoting rules
 - Least-recently basic
 - Least-recently entered
 - Least basic iterations
- Get lower bounds for the Network simplex method
- Is there a strongly polytime algorithm for LP?

The slide usually called "the end".

Thank you for listening!