

Polytope Propagation

Michael Joswig

Fachbereich Mathematik
Technische Universität Darmstadt

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Inhalt

- 1 Polytope Propagation
 - Definition and First Examples
 - The Algebraic Perspective
 - Algorithmic Issues
- 2 Algebraic Statistics
 - Statistical Models
 - Computational Biology Application
- 3 Implementation
 - polymake
 - Back to the Example



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The Setup

Consider finite directed graph $\Gamma = (V, A)$ without directed cycles and some function $\alpha : A \rightarrow \mathbb{R}^d$.

- assume a unique source $q \in V$ and a unique sink $s \in V$

Inductive construction:

- for each node $v \in V$ define polytope $P_v \subset \mathbb{R}^d$
- $P_q = 0$
- if v has the direct predecessors u_1, u_2, \dots, u_n then

$$P_v = \text{conv}(P_{u_1} + \alpha(u_1, v), \dots, P_{u_n} + \alpha(u_n, v))$$

- $P(\Gamma, \alpha) = P_s$ is the polytope *propagated* by (Γ, α)

→ Pachter & Sturmfels, 2004 & ASCB



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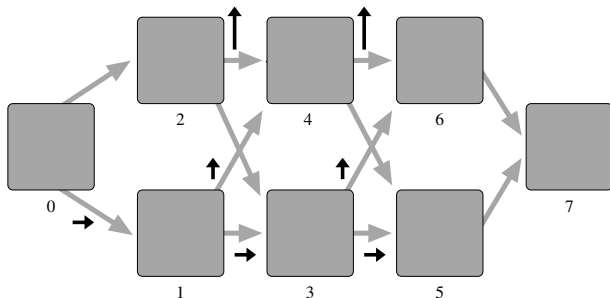
An Easy Example

$$\Gamma = (\{0, 1, \dots, 7\}, \dots)$$

$$\alpha(0, 1) = \alpha(1, 3) = \alpha(3, 5) = (1, 0),$$

$$\alpha(1, 4) = \alpha(3, 6) = (0, 1), \quad \alpha(2, 4) = \alpha(4, 6) = (0, 2),$$

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$$P(\Gamma, \alpha) = \text{conv}((0, 1), (0, 4), (1, 0), (1, 3), (3, 0))$$



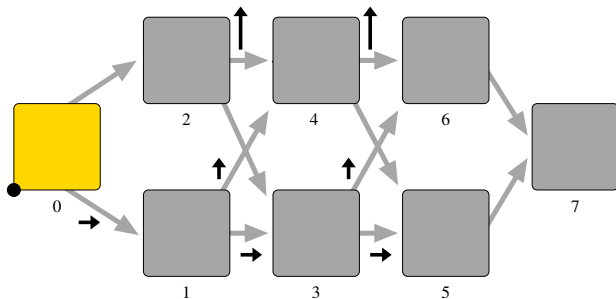
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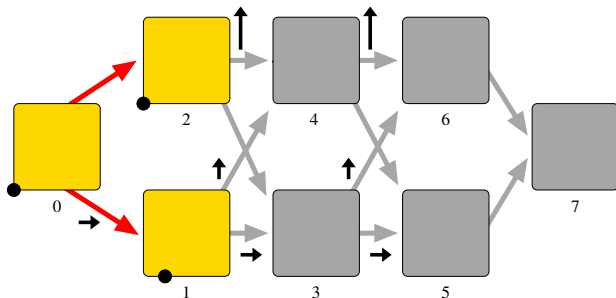
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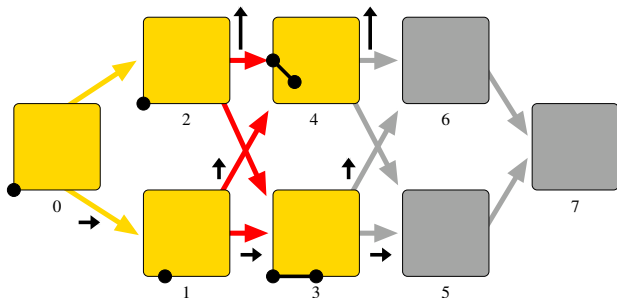
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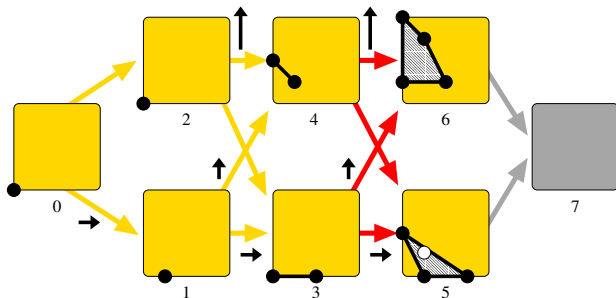
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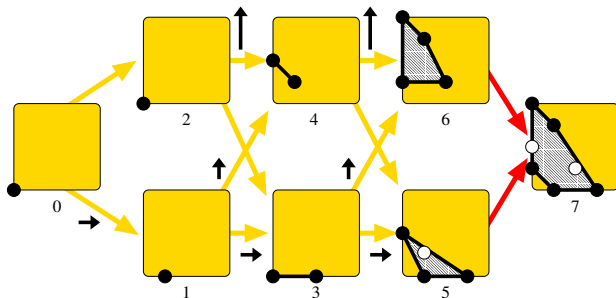
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A Trivial Example

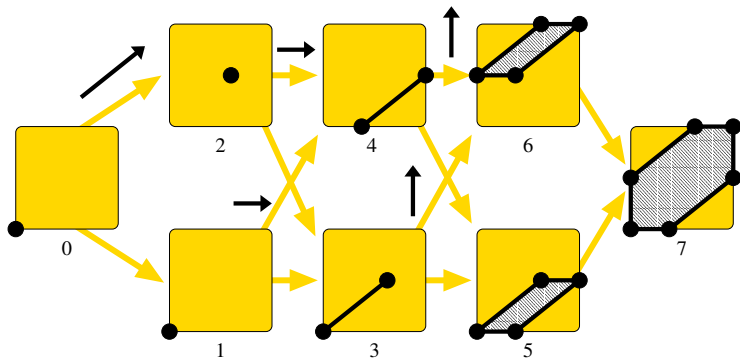
Let $\{x_1, \dots, x_n\} \subset \mathbb{R}^d$ be finite.

- Define a directed graph Θ with the $n + 2$ nodes $0, 1, \dots, n + 1$ such that there are
 - arcs from 0 to the nodes $1, 2, \dots, n$ and
 - arcs from each of the nodes $1, 2, \dots, n$ to $n + 1$.
- Further let $\theta(0, k) = x_k$ and $\theta(k, n + 1) = 0$, for $1 \leq k \leq n$.

Then 0 is the unique source, and $P(\Theta, \theta) = \text{conv}(x_1, \dots, x_n)$.



Zonotopes as Propagated Polytopes



$$[0, (2, 2)] \odot [0, (1, 0)] \odot [0, (0, 2)]$$



The Polytope Algebra

Let \mathcal{P}_d be the set of all polytopes in \mathbb{R}^d . For $P, Q \in \mathcal{P}_d$ let

$$\begin{aligned}P \oplus Q &= \text{conv}(P \cup Q) \\ &= \{\lambda p + (1 - \lambda)q \mid p \in P, q \in Q, \lambda \in [0, 1]\} \\ P \odot Q &= P + Q \\ &= \{p + q \mid p \in P, q \in Q\}\end{aligned}$$

Then $(\mathcal{P}_d, \oplus, \odot)$ is a semi-ring with idempotent addition.



The Tropical Semi-Ring

Look at the special case $\mathcal{P}_1 \dots$

- and identify $[a, b]$ with $[a - b, 0]$ for $a < b$.

Then

- $[x, 0] \oplus [y, 0] = [\min(x, y), 0]$ and
- $[x, 0] \odot [y, 0] = [x + y, 0]$.

The triplet $(\mathbb{R} \cup \{\infty\}, \min, +)$ is called the *tropical semi-ring*.



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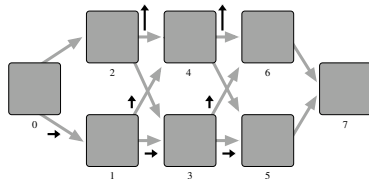
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Newton Polytopes

For $p \in K[x_1^\pm, \dots, x_d^\pm]$ let $\text{NP}(p) = \text{conv. hull of exp. vectors.}$

- $\text{NP}(p + q) = \text{NP}(p) \oplus \text{NP}(q)$,
unless cancellation arises
- $\text{NP}(pq) = \text{NP}(p) \odot \text{NP}(q)$



$$P(\Gamma, \alpha) = \text{NP}(p_7)$$

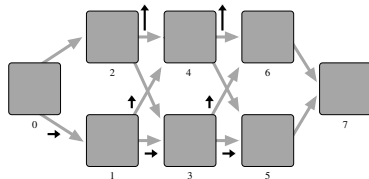
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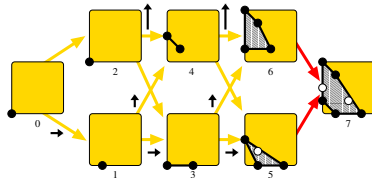
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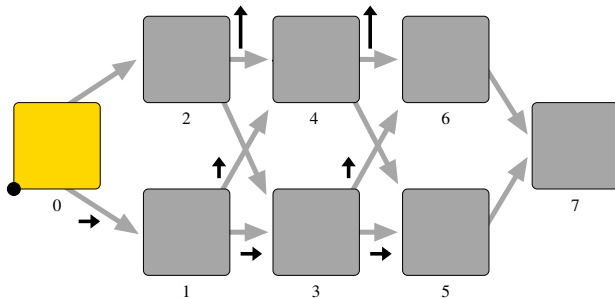


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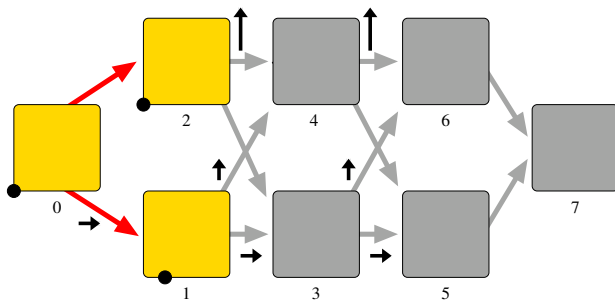
Example, continued



$$\begin{aligned} p_0 &= 1, & p_1 &= p_0 \cdot x = x, & p_2 &= p_0 \cdot 1 = 1, \\ p_3 &= p_1 \cdot x + p_2 \cdot 1 = x^2 + 1, & p_4 &= p_1 \cdot y + p_2 \cdot y^2 = xy + y^2, \\ p_5 &= p_3 \cdot x + p_4 \cdot 1 = x^3 + xy + x + y^2, \\ p_6 &= p_3 \cdot y + p_4 \cdot y^2 = x^2y + xy^3 + y + y^4, \\ p_7 &= p_5 \cdot 1 + p_6 \cdot 1 = x^3 + x^2y + xy + xy^3 + x + y + y^2 + y^4 \end{aligned}$$



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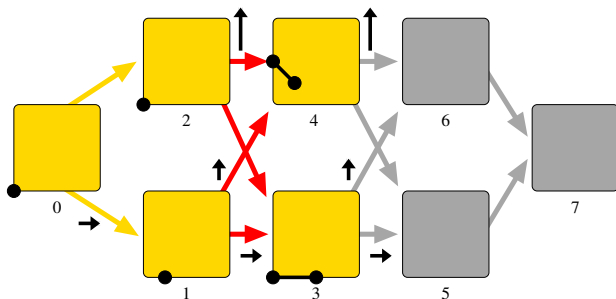
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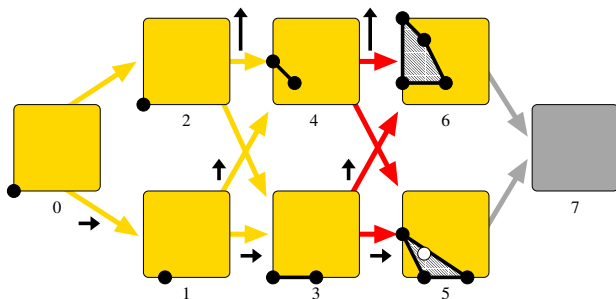
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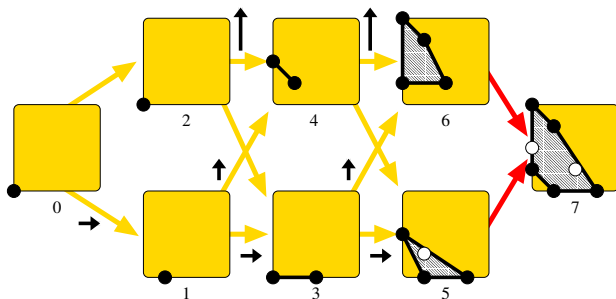
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Output-Sensitivity

Define $\text{size}(\Gamma, \alpha)$ as the combined sizes of V -representations of all intermediate polytopes.

Theorem. The vertices of $P(\Gamma, \alpha)$ can be computed in time which is polynomially bounded in $\text{size}(\Gamma, \alpha)$.

Proof. Linear optimization gives polynomial time oracle for separation.

- zonotopes
- Andrews, 1962: number of vertices of lattice polytope polynomially bounded by volume



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Hidden Markov Models

Finite (*primary*) Markov process with l states and transition matrix $\theta = (\theta_{ij}) \in \mathbb{R}^{l \times l}$ with $\theta_{ij} \geq 0$ and $\sum_j \theta_{ij} = 1$.

Observation as a probabilistic function of the state!

- l' possible observations (where l' may be different from l)
- non-negative matrix

$$\theta' = (\theta'_{ij}) \in \mathbb{R}^{l \times l'}$$

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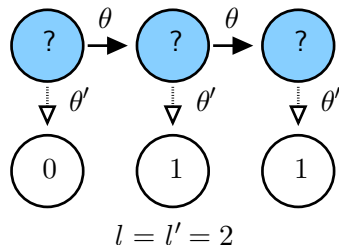
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Let $l = l' = 2$ (state space $\{0, 1\}$; initial distribution uniform),

$$\theta = \begin{pmatrix} \theta_{00} & \theta_{01} \\ \theta_{10} & \theta_{11} \end{pmatrix}, \quad \text{and} \quad \theta' = \begin{pmatrix} \theta'_{00} & \theta'_{01} \\ \theta'_{10} & \theta'_{11} \end{pmatrix}.$$

Observe primary process for $n = 3$ steps: $\beta_1\beta_2\beta_3 \in \{0, 1\}^3$:

$$\text{Prob}[Y_1 = \beta_1, Y_2 = \beta_2, Y_3 = \beta_3] =$$

$$\frac{1}{2} \sum_{\sigma \in \{0,1\}^3} \theta_{\sigma_1\sigma_2} \theta_{\sigma_2\sigma_3} \theta'_{\sigma_1\beta_1} \theta'_{\sigma_2\beta_2} \theta'_{\sigma_3\beta_3}$$

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Parameterized Models: Overly Simplified Example

- $l = l' = 2$ and $\theta = \theta' = \begin{pmatrix} u & v \\ v & w \end{pmatrix}$ symmetric
- assume $v \neq 0$ (otherwise primary process stationary)
- neglecting probabilistic constraints and re-scaling:

$$\hat{\theta} = \hat{\theta}' = \begin{pmatrix} x & 1 \\ 1 & y \end{pmatrix} \in \mathbb{R}[x, y]^{2 \times 2}$$

Treat x, y as indeterminates!

Probability to make the specific observation 011:

$$\text{Prob}[Y_1 = 0, Y_2 = 1, Y_3 = 1] =$$

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$$\text{Prob}[Y_1 = 0, Y_2 = 1, Y_3 = 1] =$$

$$\frac{1}{2}(x^3 + x^2y + xy + xy^3 + x + y + y^2 + y^4)$$



Parameterized Models: Overly Simplified Example

- $l = l' = 2$ and $\theta = \theta' = \begin{pmatrix} u & v \\ v & w \end{pmatrix}$ symmetric
- assume $v \neq 0$ (otherwise primary process stationary)
- neglecting probabilistic constraints and re-scaling:

$$\hat{\theta} = \hat{\theta}' = \begin{pmatrix} x & 1 \\ 1 & y \end{pmatrix} \in \mathbb{R}[x, y]^{2 \times 2}$$

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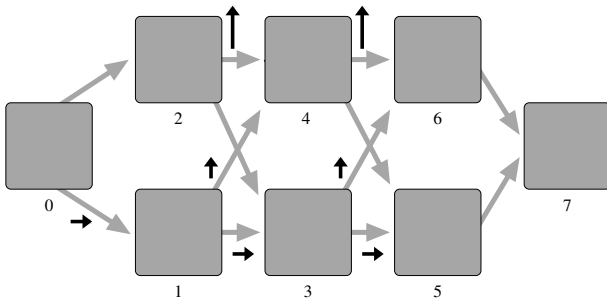


Polytope Propagation

Observation β gives graph $\Gamma = \text{observation path} \times \text{state space}$ and

$$\alpha[(i-1, j) \rightarrow (i, k)] = \text{NP}(\theta_{jk}\theta'_{k,\beta_i}),$$

since $\text{Prob}[X_{i-1} = j, X_i = k | Y_i = \beta_i] = \theta_{jk}\theta'_{k,\beta_i}$. **here: monomial!**



Explanation of $\beta = \text{directed path} = \text{point in NP}(\text{Prob}[Y = \beta])$.

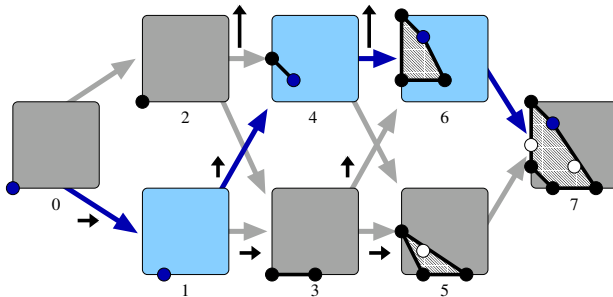


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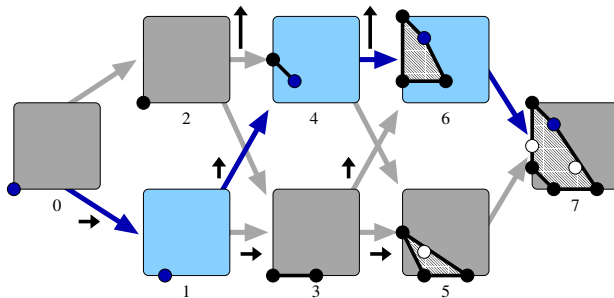


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Parametric Sequence Alignment

Fitch & Smith, 1983; Dewey & Woods, 2005

Two mRNA alignments of two variants of chicken hemoglobin.
Either

β : UUUGCGUCCUUUGGGAACCUCUCCAGCCCCA...
 α : UUUCCCCACUUC---GAUCUGUCACAC-----...

or

β : UUUGCGUCCUUUGGGAACCUCUCCAGCCCCA...
 α : UUUCCCCACUUCG---AUCUGUCACAC-----...

?

Adenine, Cytosine, Guanine, Uracil



Overview

since 1997 w/ Evgenij Gawrilow
and contributions by Thilo Schröder & Niko Witte (et al.)

- convex polytopes
 - analysis of combinatorial and geometric properties
 - constructions & visualization
- TOPology Application Zoo
 - simplicial (co-)homology with coefficients in \mathbb{Z} and $\text{GF}(2)$
 - intersection forms (of 4-manifolds), Stiefel-Whitney characteristic classes, etc.
- tropical geometry [prototype]

> 50 000 uloc C++/Perl www.math.tu-berlin.de/polymake



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Perl Scripts in Version 2.1

```
application 'polytope';  
die "usage: polymake --script ... \n" unless @ARGV;  
my $p=load($ARGV[0]);  
my @list=();  
  
FACETS:  
for (my $i=0; $i< $p->N_FACETS ; ++$i) {  
    my $facet=new Apps::polytope::RationalPolytope("...");  
    Modules::client("facet", $facet, $p, $i, "-relabel");  
    foreach my $other_facet (@list) {  
        next FACETS if ( check_iso($facet, $other_facet) );  
    }  
    push @list, $facet;  
}  
  
static_javaview;  
$_->VISUAL_GRAPH for @list;
```



Example, continued

```
> binary-markov-graph b011.poly 011
```

```
> polymake b011.poly "numbered(SUM_PRODUCT_GRAPH)"  
numbered(SUM_PRODUCT_GRAPH)
```

```
0:{(1 1 0) (2 0 0)}
```

```
1:{(3 1 0) (4 0 1)}
```

```
2:{(3 0 0) (4 0 2)}
```

```
3:{(5 1 0) (6 0 1)}
```

```
4:{(5 0 0) (6 0 2)}
```

```
5:{(7 0 0)}
```

```
6:{(7 0 0)}
```

```
7:{ }
```



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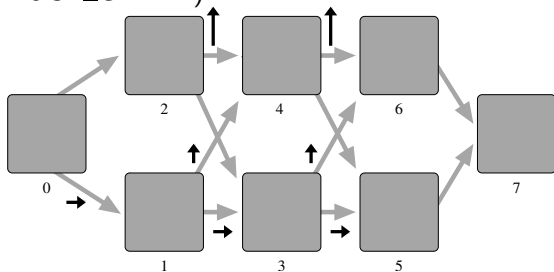
```
3:{(5 1 0) (6 0 1)}
```

```
4:{(5 0 0) (6 0 2)}
```

```
5:{(7 0 0)}
```

```
6:{(7 0 0)}
```

```
7:{ }
```



Example, the End

```
> sum_product b011.poly  
> polymake b011.poly "numbered(VERTICES)"\  
"numbered(VERTEX_NORMALS)"
```

```
numbered(VERTICES)
```

```
0:1 3 0
```

```
1:1 1 0
```

```
2:1 0 1
```

```
3:1 1 3
```

```
4:1 0 4
```

```
numbered(VERTEX_NORMALS)
```

```
0:0 1/2 0
```

```
1:0 -1/2 -3/2
```

```
2:0 -2 -1
```

```
3:0 4 3
```

```
4:0 -1/2 1/2
```

Vertex $(1, 3)$ corresponds to ...

- path $0 \rightarrow 1 \rightarrow 4 \rightarrow 6 \rightarrow 7$
- state sequence 011 in primary process

If we are to maximize $4x + 3y$,
then we can trust our
observation 011.



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```
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```

```
2:1 0 1
```

```
3:1 1 3
```

```
4:1 0 4
```

```
numbered(VERTEX_NORMALS)
```

```
0:0 1/2 0
```

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