



Introduction to Dynamic Programming for Generative Models

Andreas Stuhlmüller
IPAM GSS 2011

Overview

- Motivation
 - A simple coordination game
 - Blue-eyed islanders puzzle
 - Hidden Markov models
- DP for HMMs: Forward and Viterbi algorithm
- DP for probabilistic programs: UDP algorithm

A simple coordination game

```
(define (sample-location)
  (if (flip .55)
    'popular-bar
    'unpopular-bar))
```

```
(define (bob)
  (sample-location))
```



(Schelling 1960)

A simple coordination game

```
(define (sample-location)
  (if (flip .55)
    'popular-bar
    'unpopular-bar))

(define (alice)
  (query
    (define alice-location (sample-location))
    alice-location
    (equal? alice-location (bob)))))

(define (bob)
  (sample-location))
```



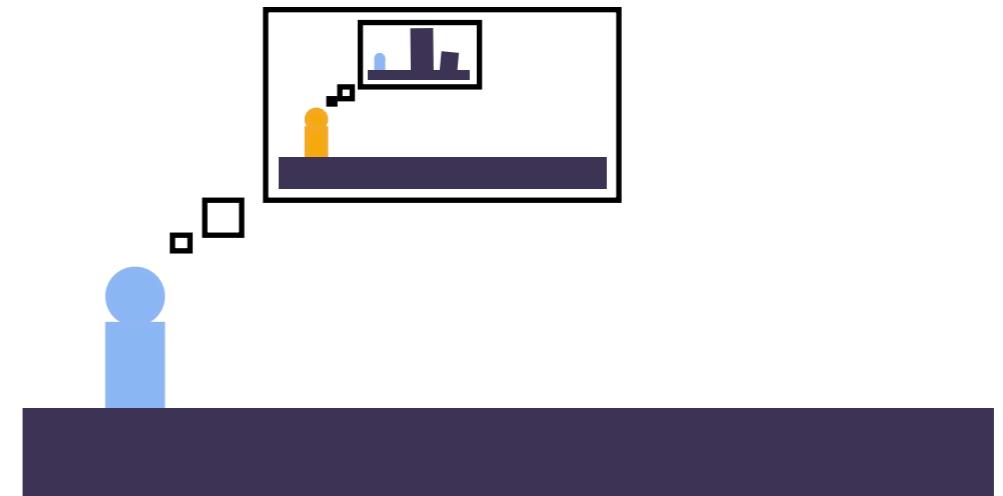
(Schelling 1960)

A simple coordination game

```
(define (sample-location)
  (if (flip .55)
    'popular-bar
    'unpopular-bar))

(define (alice depth)
  (query
    (define alice-location (sample-location))
    alice-location
    (equal? alice-location (bob (- depth 1)))))

(define (bob depth)
  (query
    (define bob-location (sample-location))
    bob-location
    (or (= depth 0)
        (equal? bob-location (alice depth)))))
```

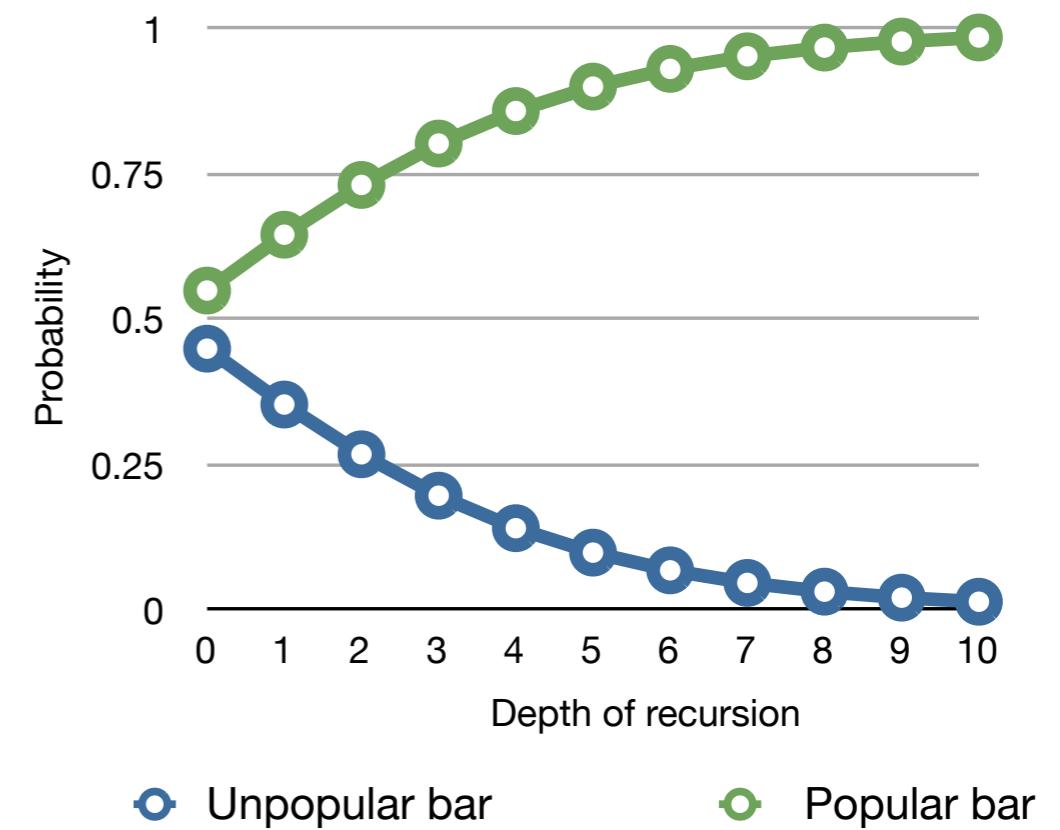


A simple coordination game

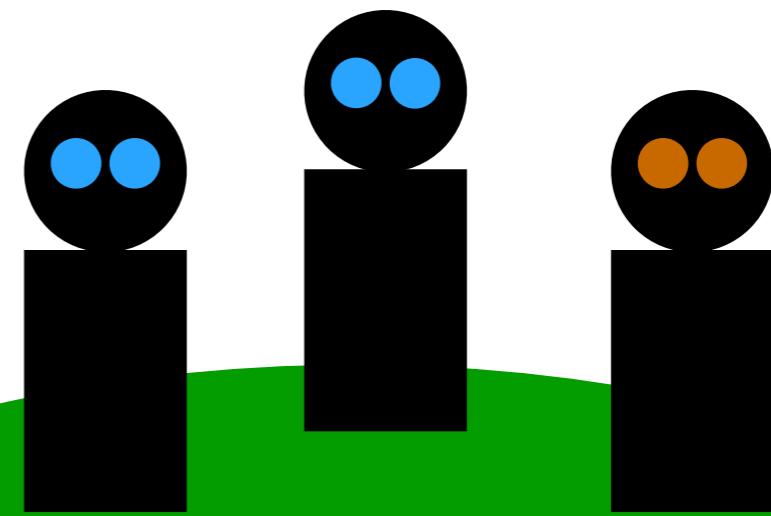
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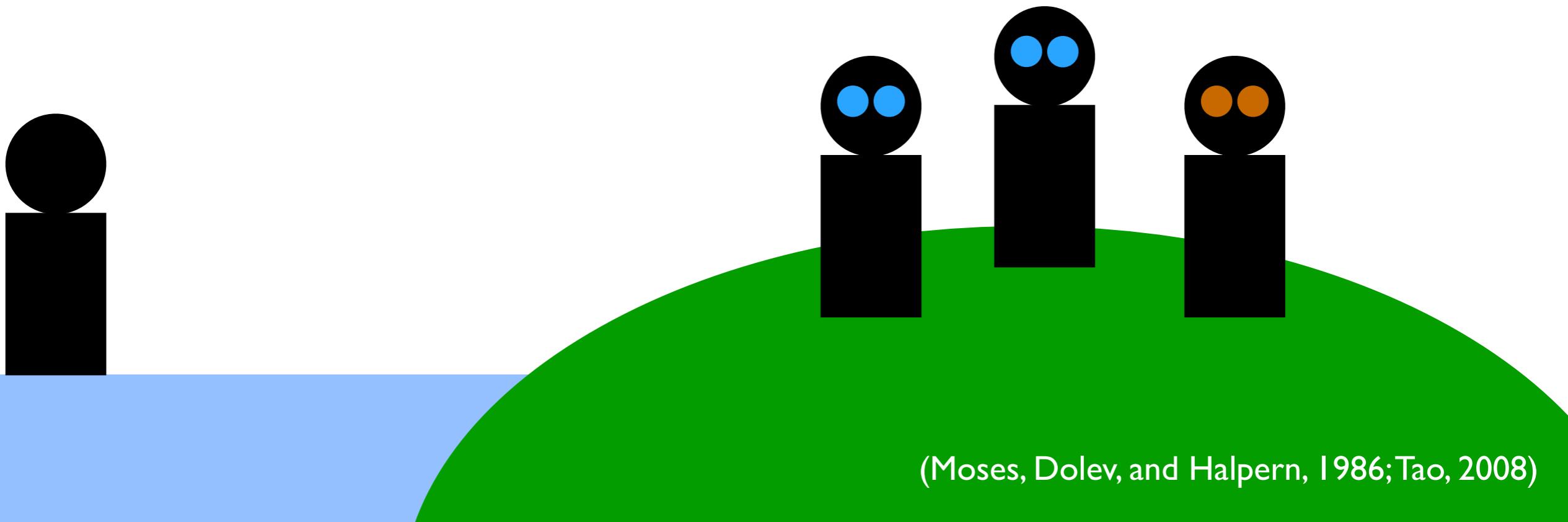


The blue-eyed islanders puzzle



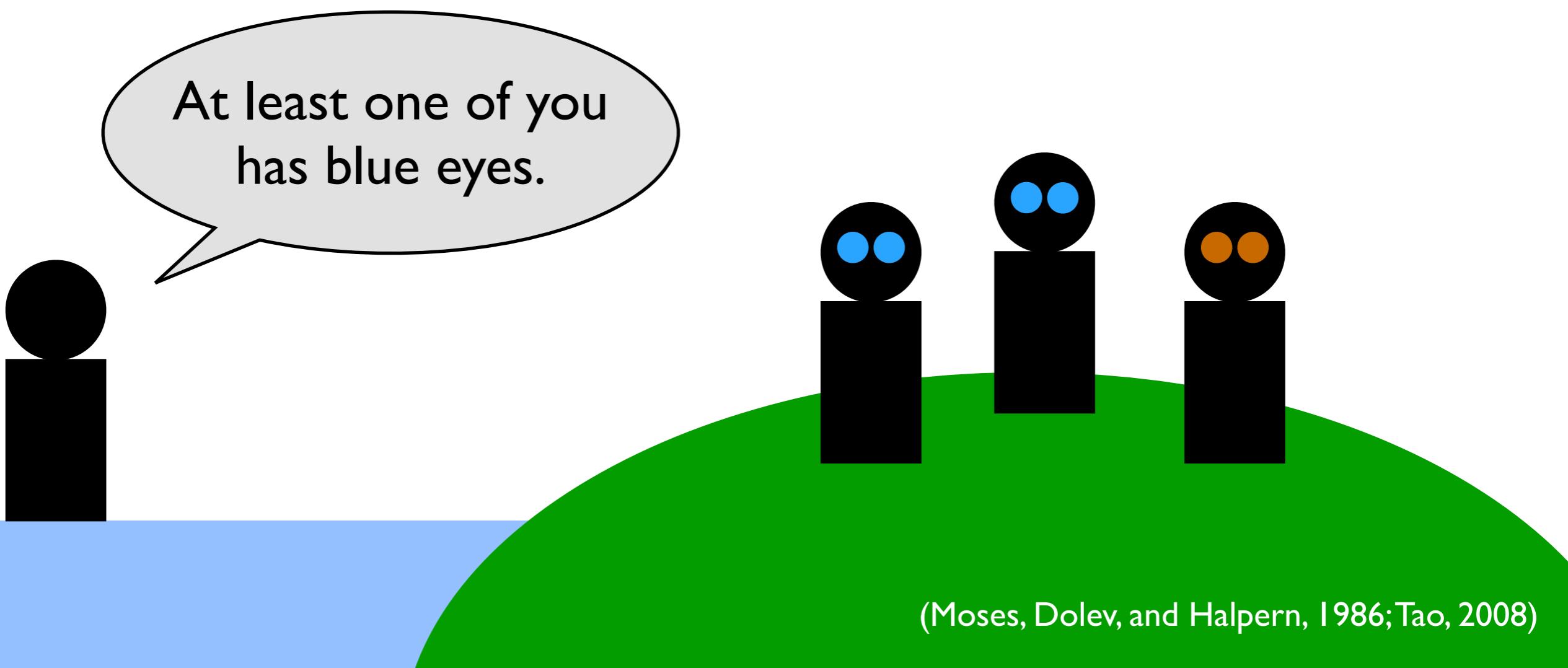
(Moses, Dolev, and Halpern, 1986; Tao, 2008)

The blue-eyed islanders puzzle



(Moses, Dolev, and Halpern, 1986; Tao, 2008)

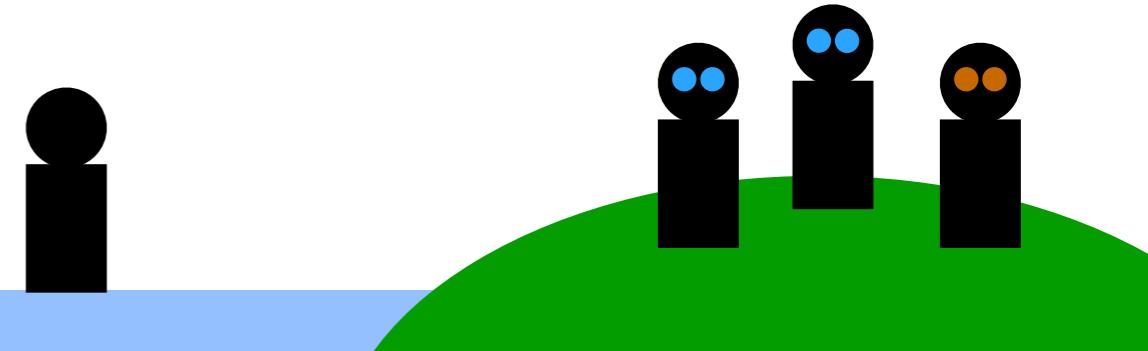
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The blue-eyed islanders puzzle

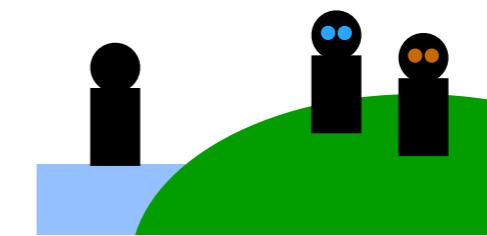
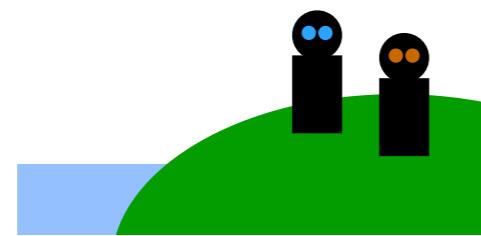
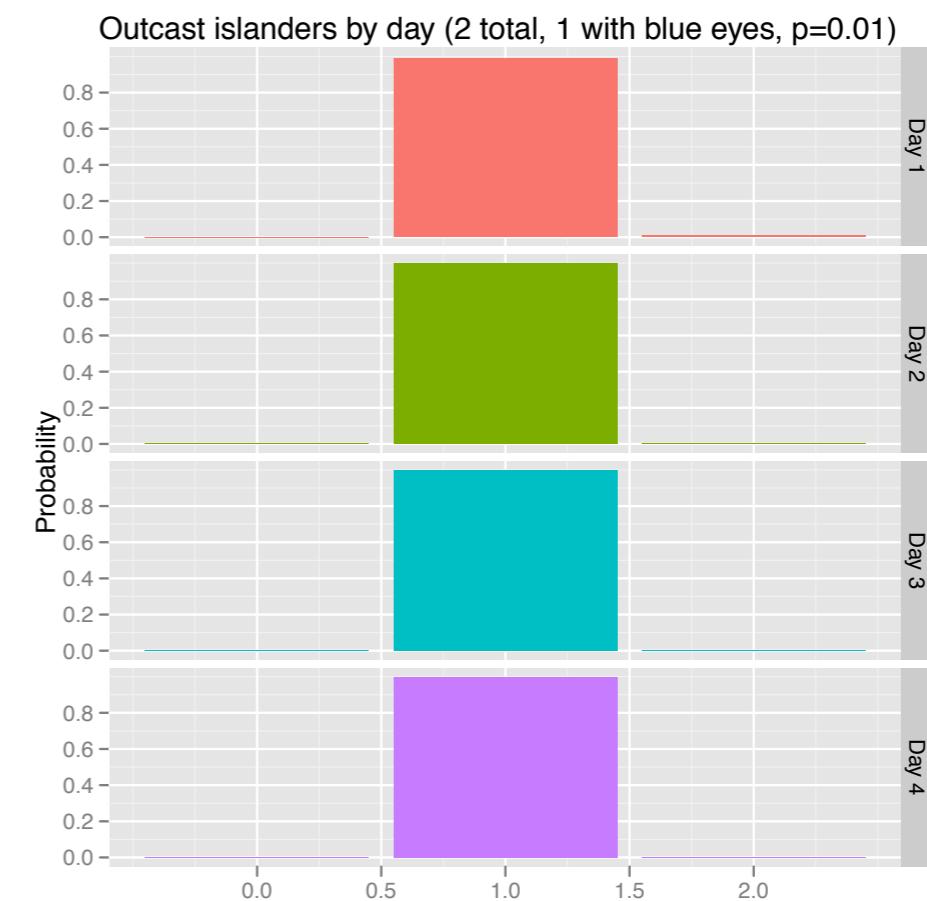
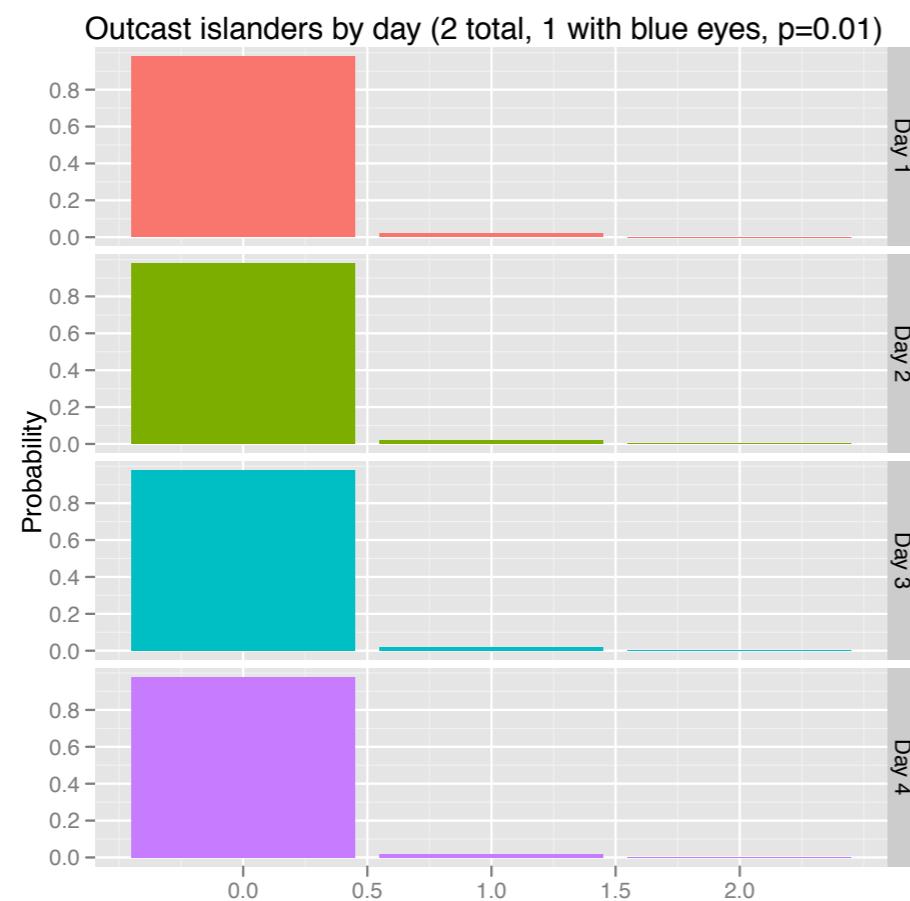
- Two arguments:
 - “The outsider provides no new information, therefore nothing changes.”
 - “By induction on the number of blue-eyed people, all N blue-eyed people leave on day N .”



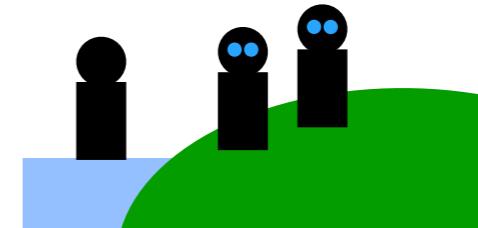
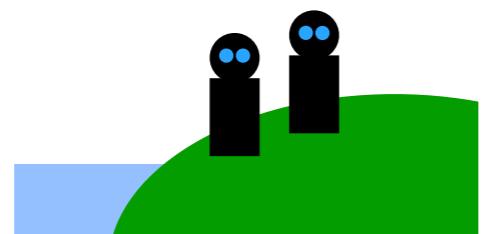
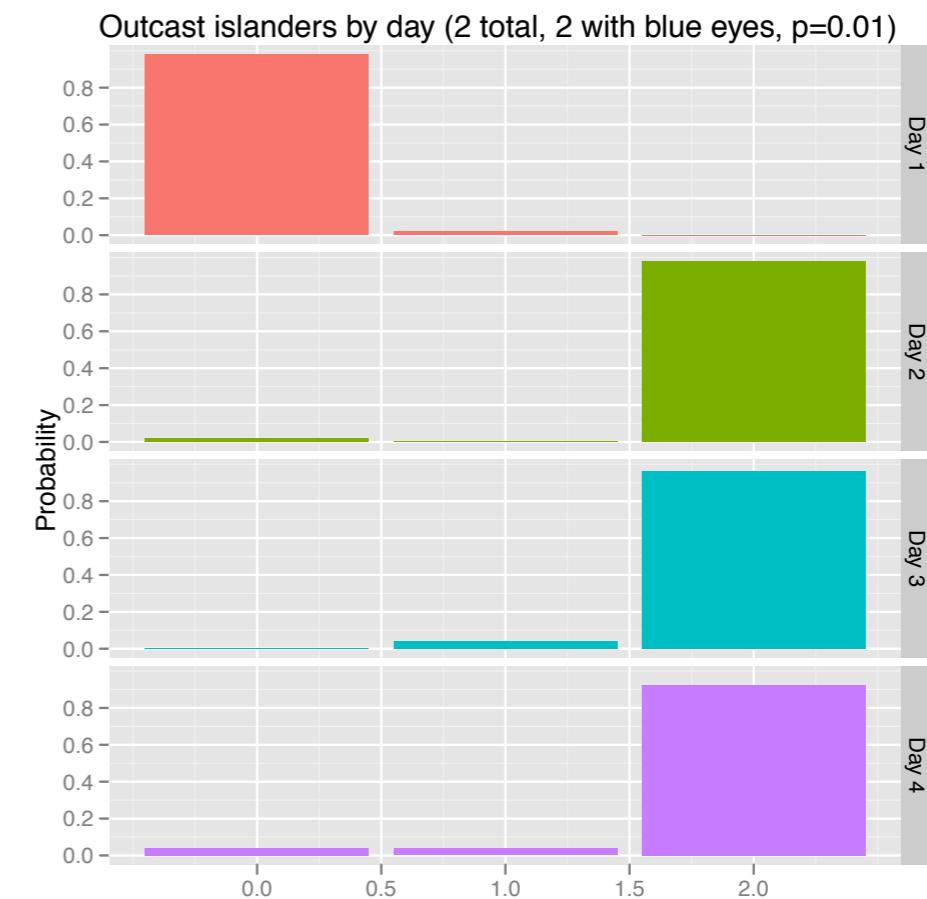
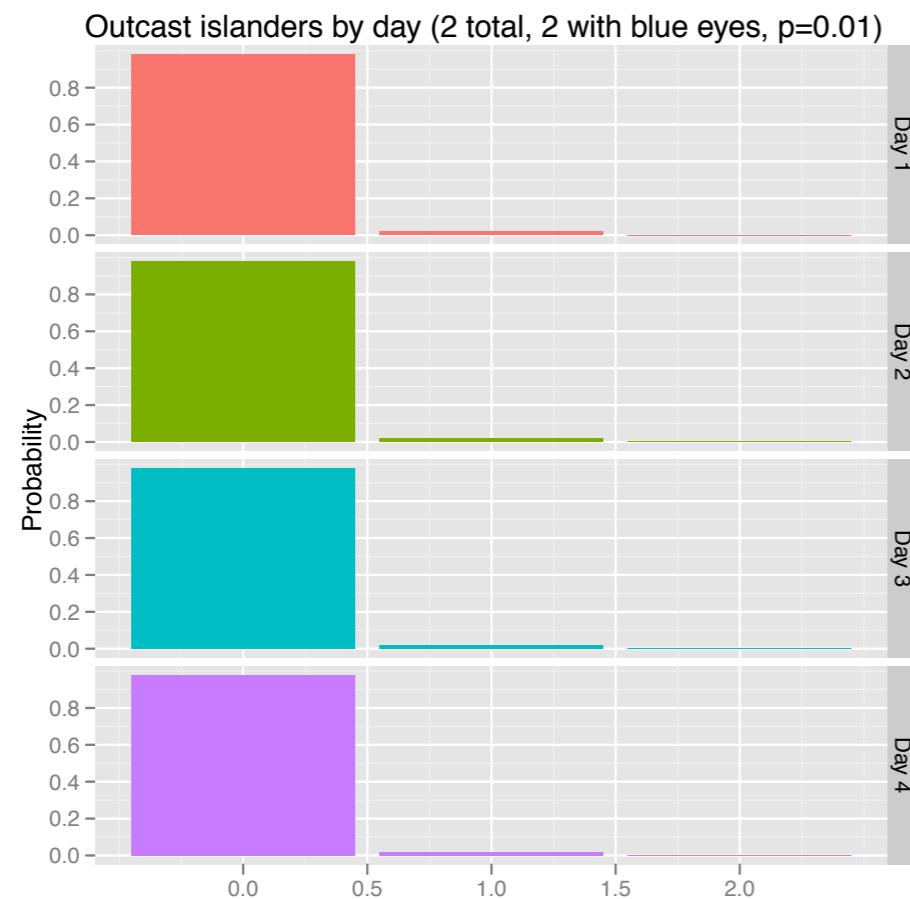
The blue-eyed islanders puzzle

- Difficult for current universal inference algorithms
 - Deeply nested queries
 - Complex (almost-)deterministic dependencies
- But: Potential for sharing of subcomputations

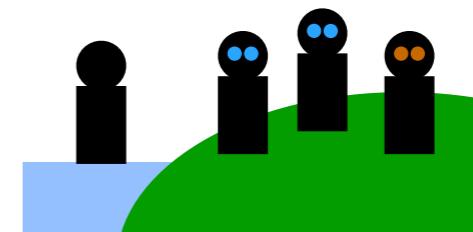
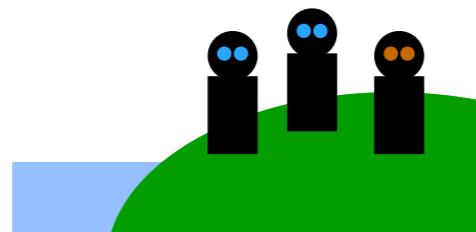
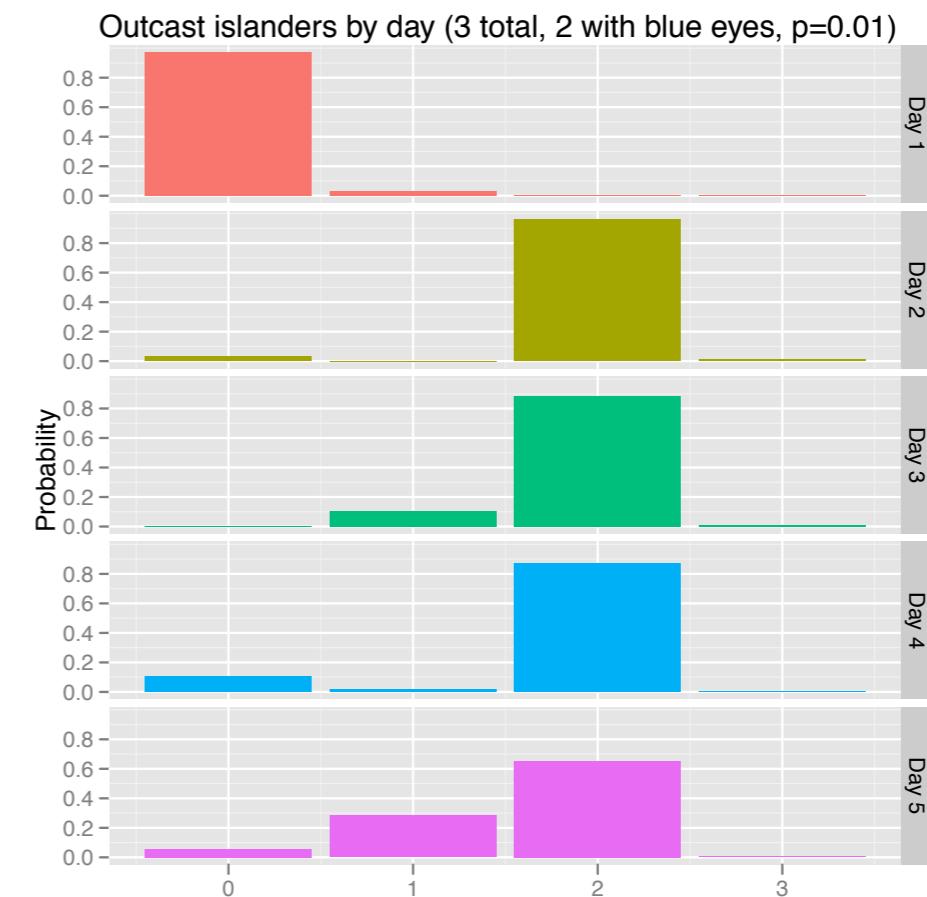
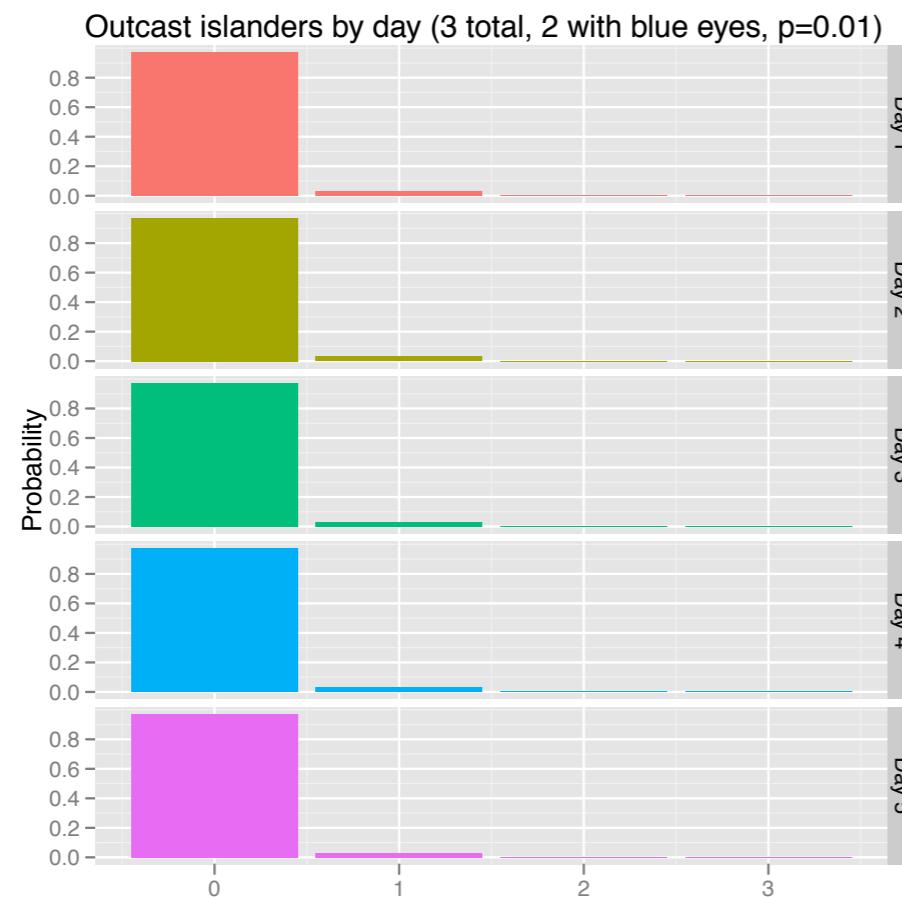
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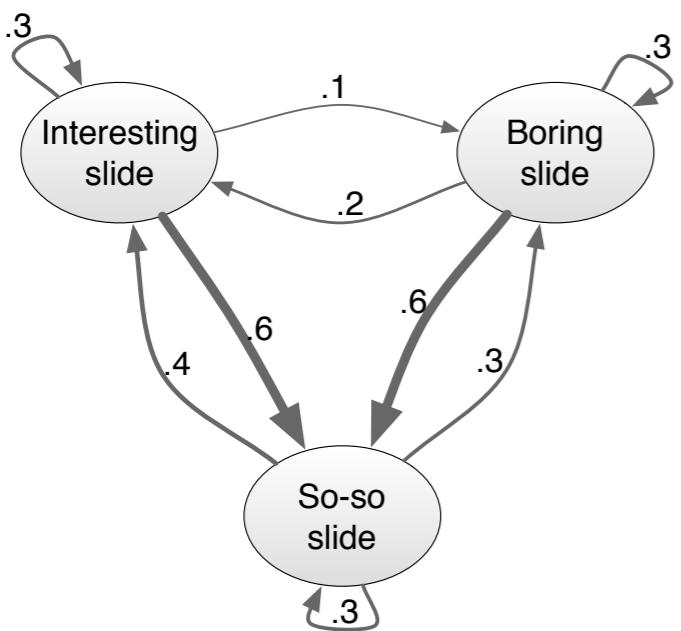
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The blue-eyed islanders puzzle

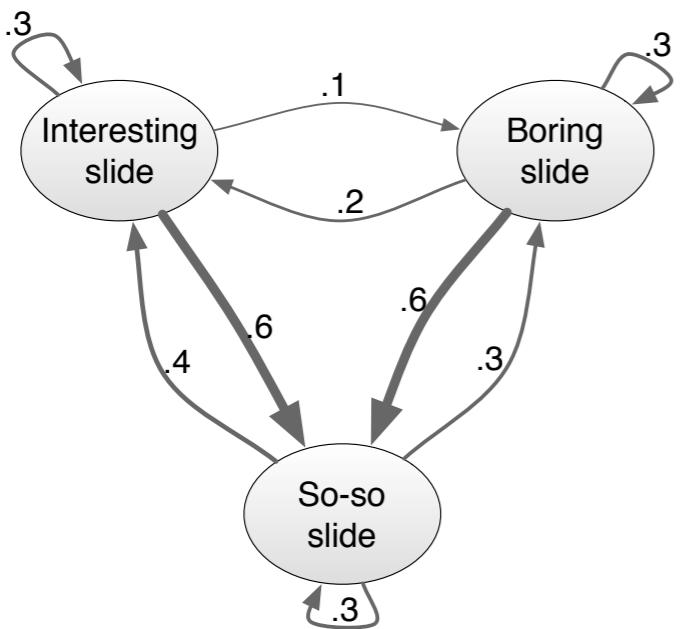


Markov Models



- Set of states $Q = \{S_+, S_0, S_-\}$
- Transition probability matrix A
- Distribution on initial states P_{init}
- Set of end states Q_{end}

Markov Models

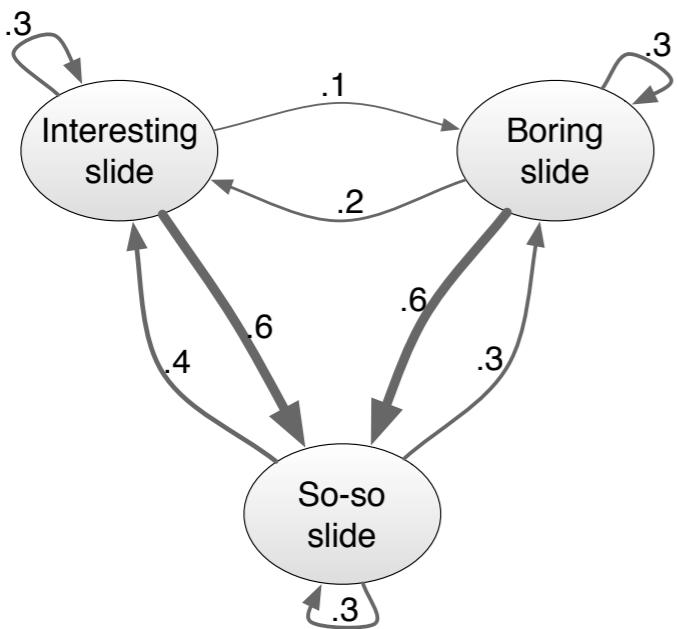


- Set of states $Q = \{S_+, S_0, S_-\}$
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Markov assumption:

$$P(q_i | q_1, \dots, q_{i-1}) = P(q_i | q_{i-1})$$

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So-so

Overview

- Motivation
 - Blue-eyed islanders puzzle
 - Hidden Markov models
 - Exact Inference
 - Dynamic Programming
 - Viterbi Algorithm
 - UDP Algorithm

So-so

The blue-eyed islanders puzzle

At least one of you has blue eyes.

Interesting

The blue-eyed islanders puzzle

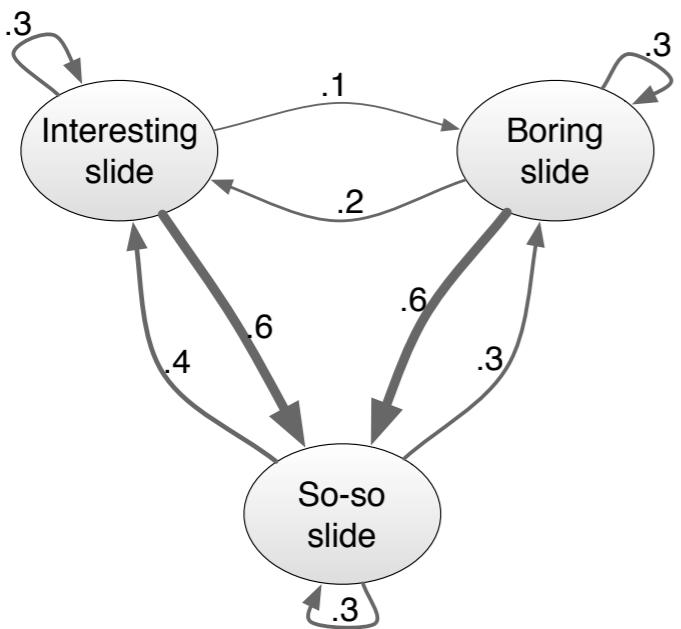
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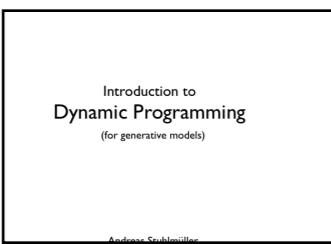
Markov Models



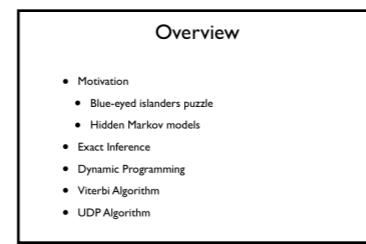
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$$P([S_0, S_0, S_+, S_+, S_0]) =$$

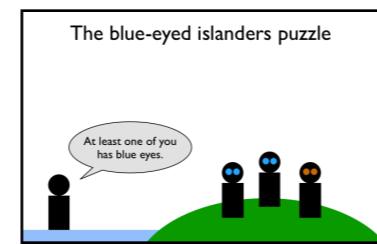
$$P_{init}(S_0) * P(S_0|S_0) * P(S_+|S_0) * P(S_+|S_+) * P(S_0|S_+)$$



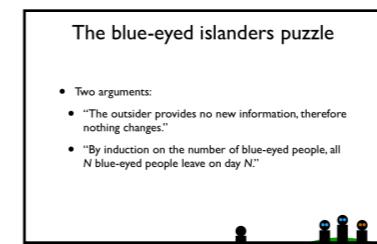
So-so



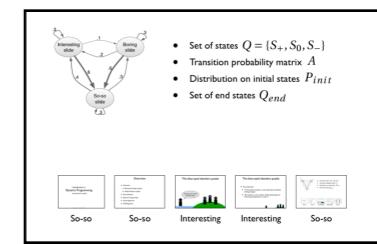
So-so



Interesting

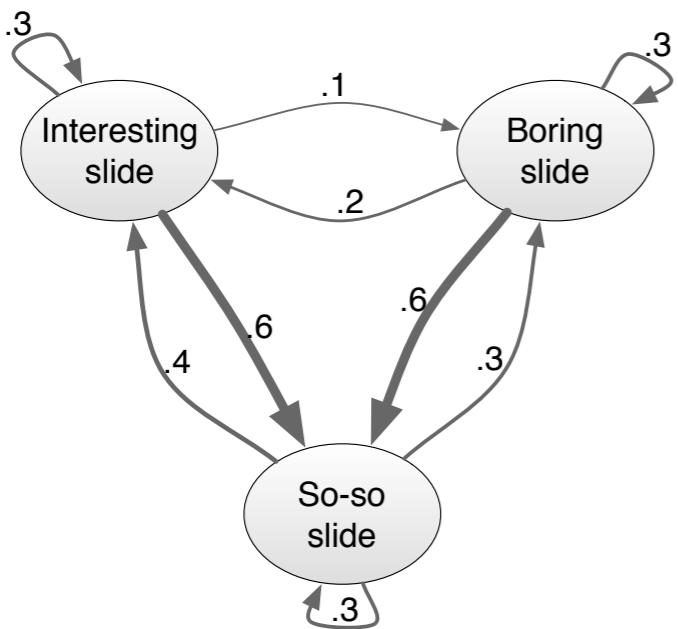


Interesting



So-so

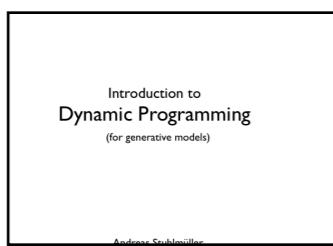
Markov Models



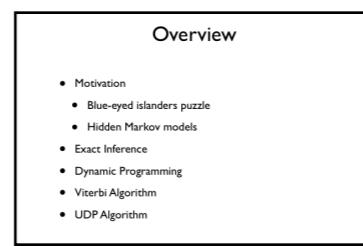
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$$P([S_0, S_0, S_+, S_+, S_0]) =$$

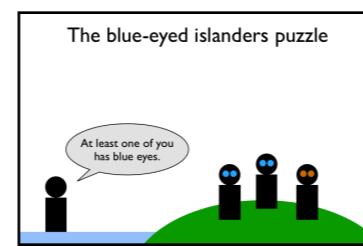
$$.33 * .3 * .4 * .3 * .6 = .0071$$



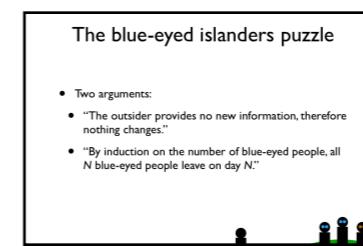
So-so



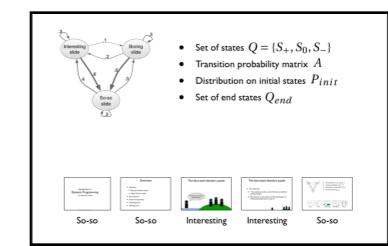
So-so



Interesting

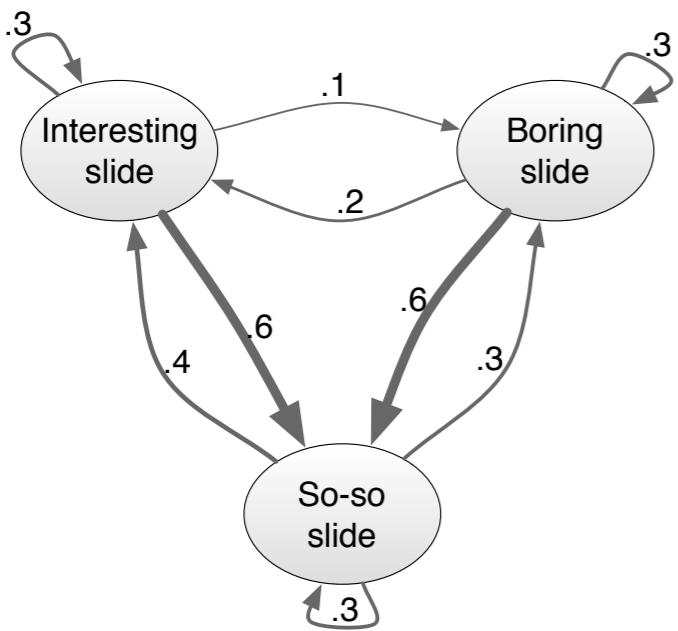


Interesting



So-so

Markov Models



```
(define transition-dists
  '((interesting . (.3 .6 .1))
    (so-so . (.4 .3 .3))
    (boring . (.2 .6 .3))))
```

```
(define (transition state)
  (multinomial '(interesting so-so boring)
    (rest (assoc state transition-dists))))
```

```
(define (mm state n)
  (if (= n 0)
    '()
    (pair state
      (mm (transition state) (- n 1)))))
```

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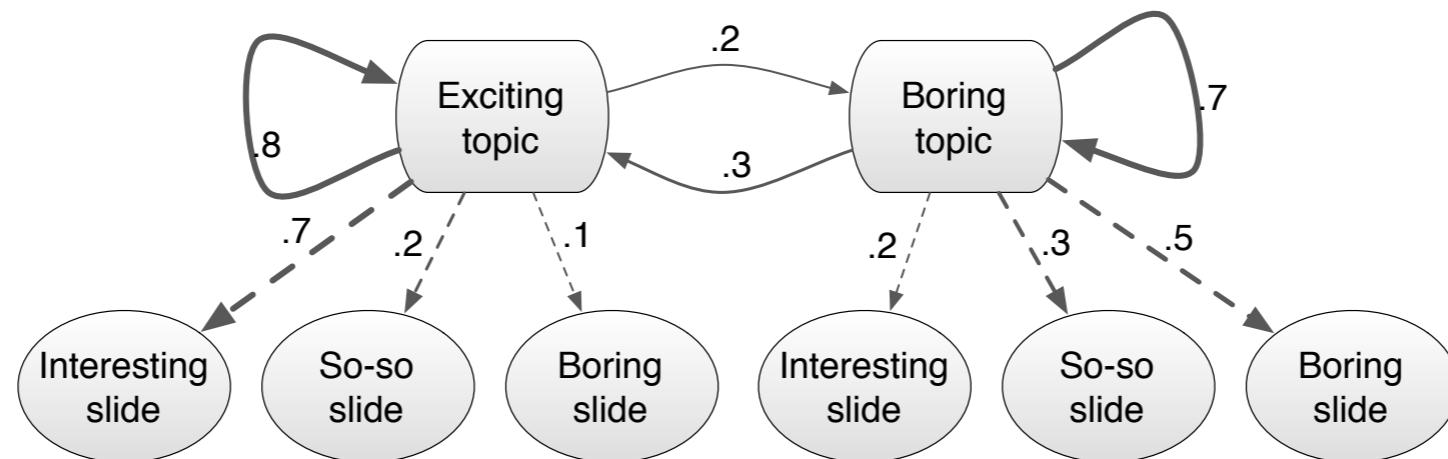
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So-so So-so Interesting Interesting So-so

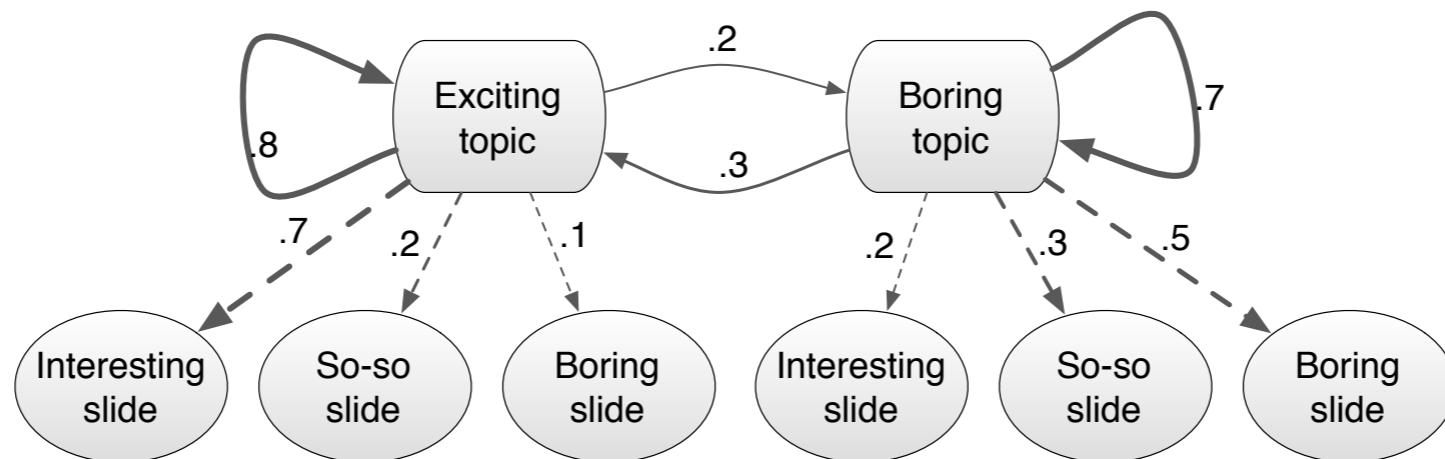
So-so

Hidden Markov Models



- Set of states $Q = \{E, \neg E\}$
- Transition probability matrix A
- Distribution on initial states P_{init}
- Set of end states Q_{end}
- Set of possible observations $V = \{S_+, S_0, S_-\}$
- Observation probability matrix O

Hidden Markov Models

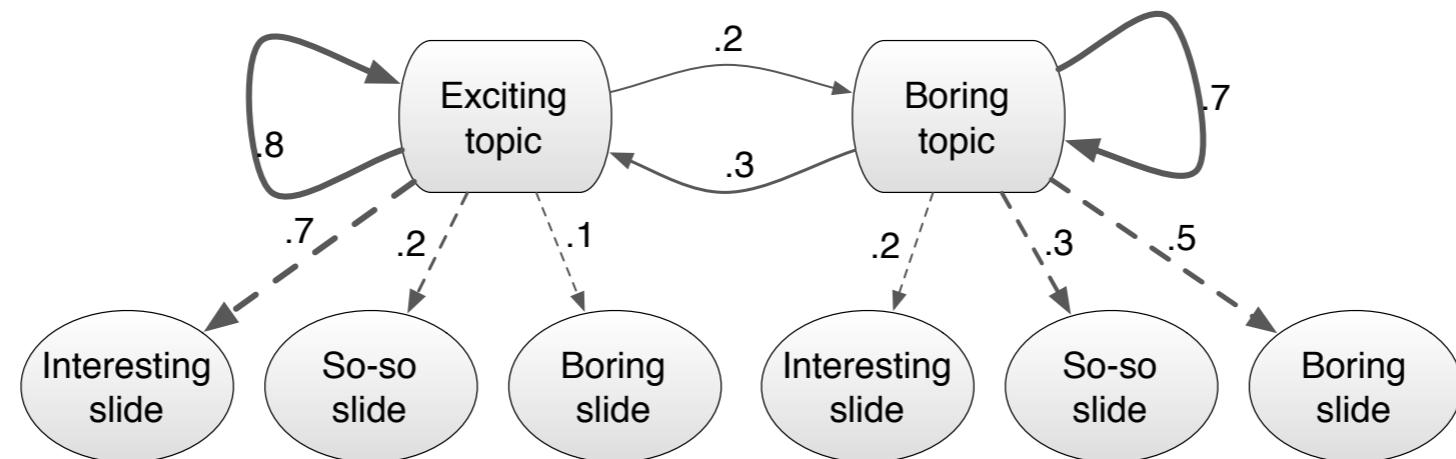


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Markov assumption: $P(q_i | q_1, \dots, q_{i-1}) = P(q_i | q_{i-1})$

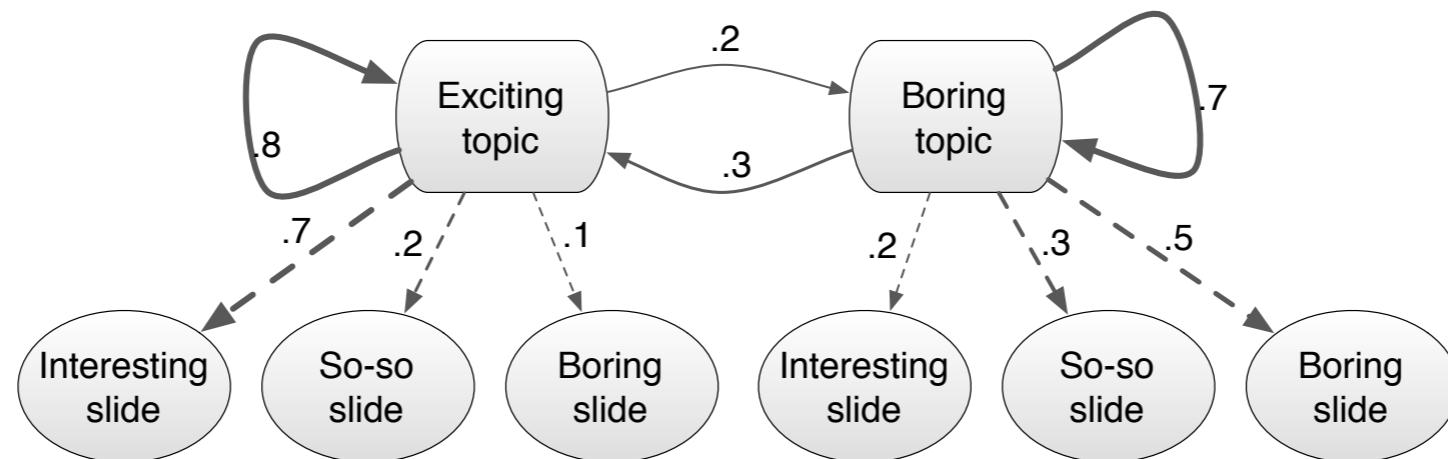
Output independence: $P(o_i | q_1, \dots, q_i, \dots, q_T) = P(o_i | q_i)$

Hidden Markov Models



```
(define (mm state n)
  (if (= n 0)
    '()
    (pair state
      (mm (transition state) (- n 1))))))
```

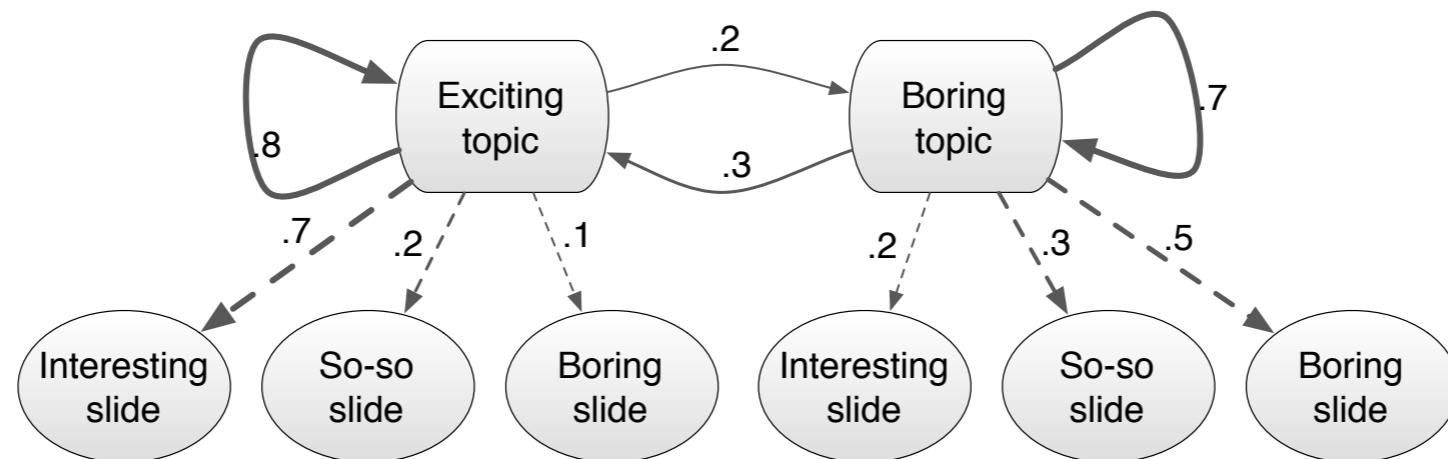
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```
(define (hmm state n)
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```

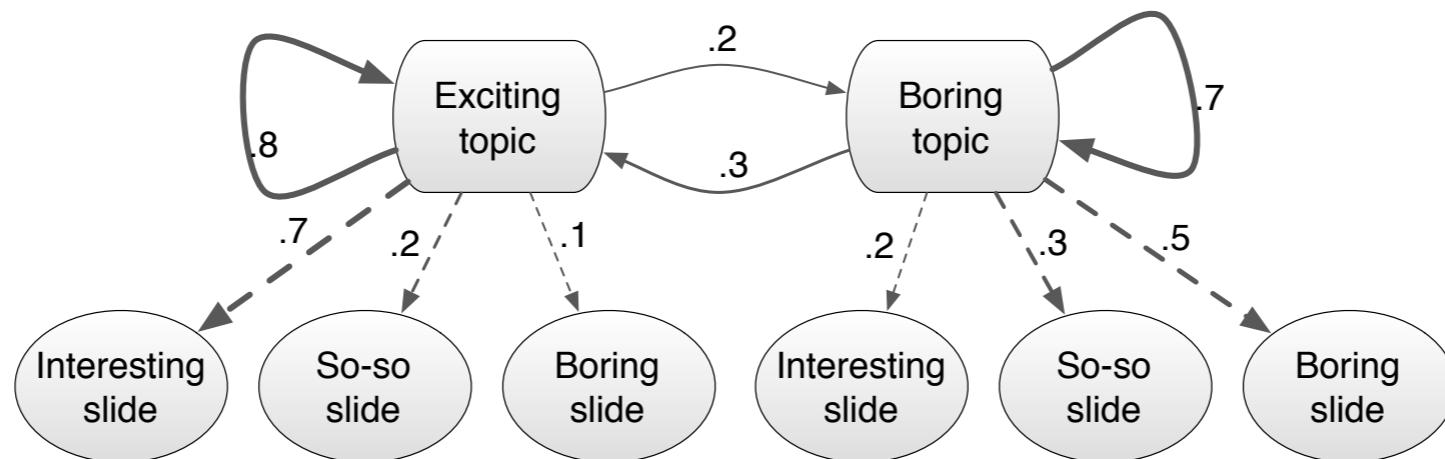
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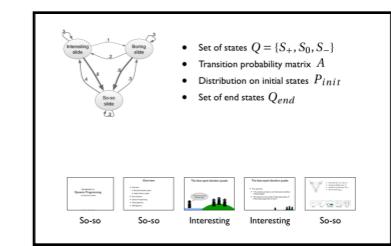
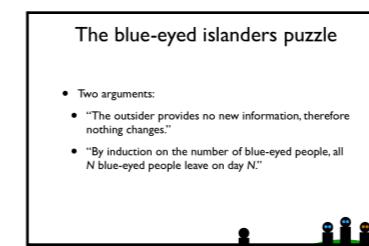
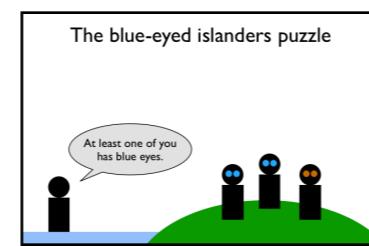
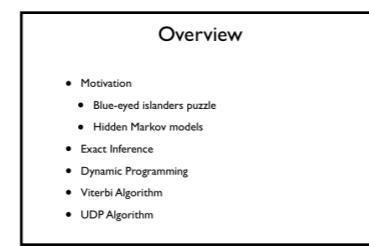
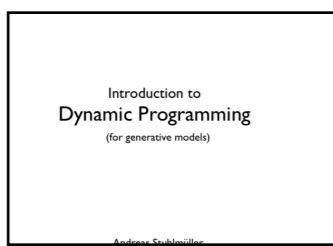
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So-so

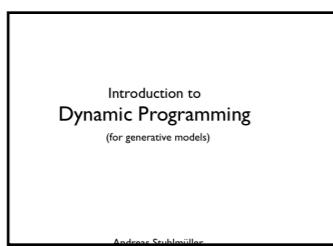
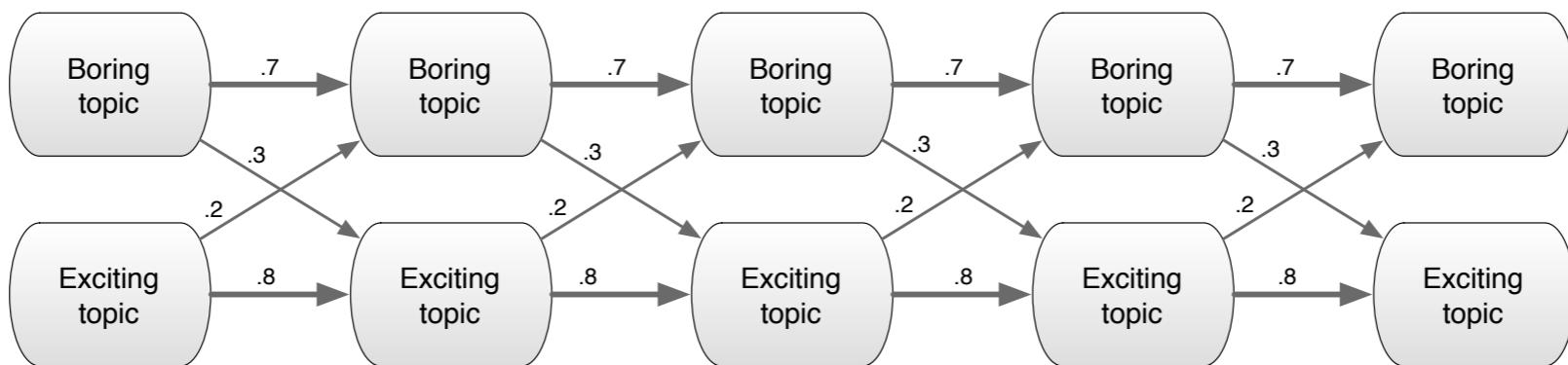
So-so

Interesting

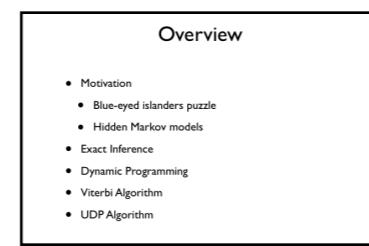
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So-so

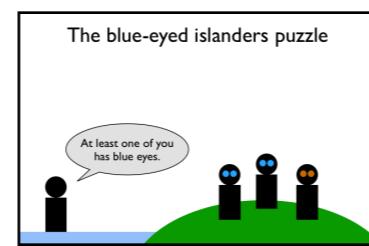
Inference by Enumeration



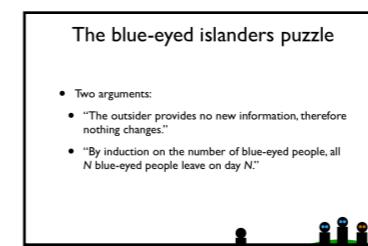
So-so



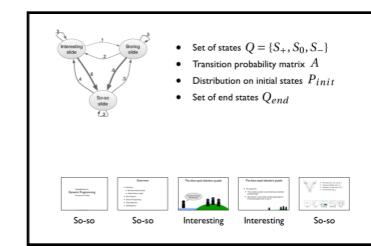
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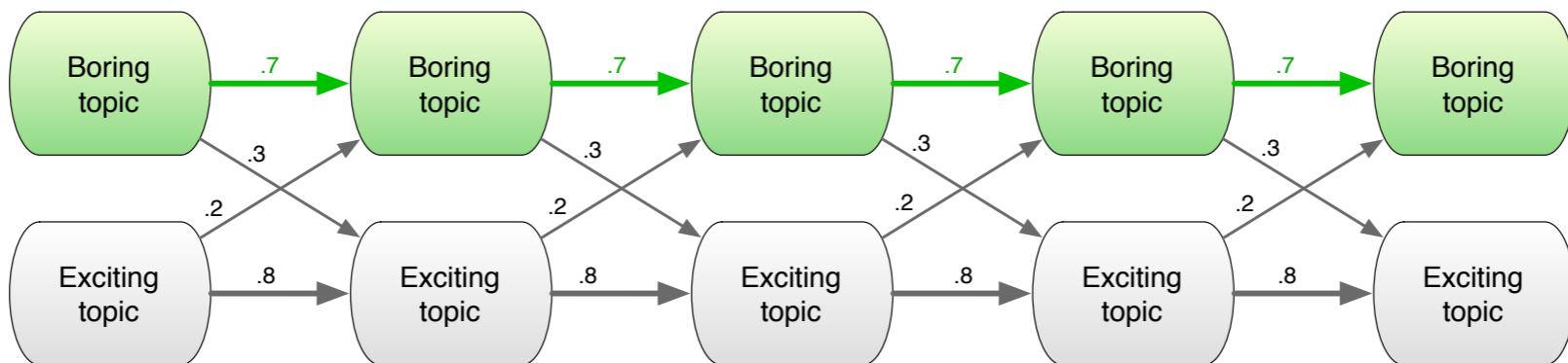


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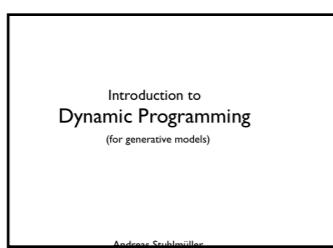


So-so

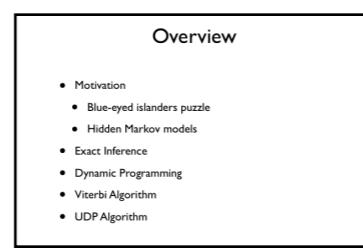
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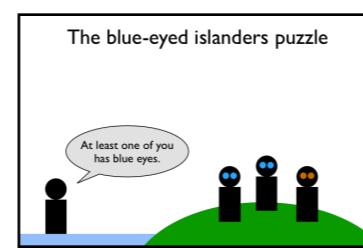
$$P(o_{1:n}|q_{1:n}) = P(o_n|q_n) \dots P(o_1|q_1)$$



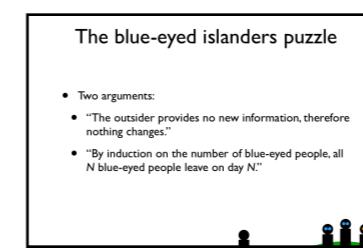
So-so



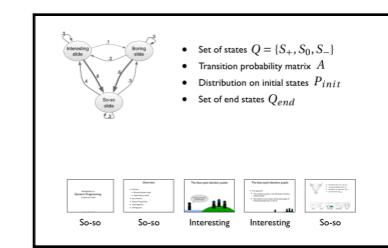
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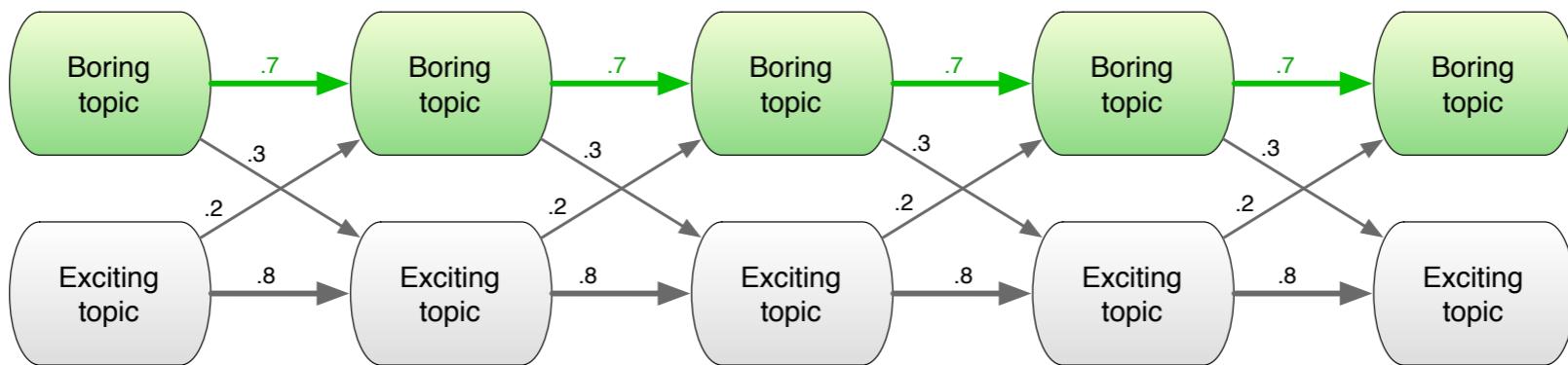


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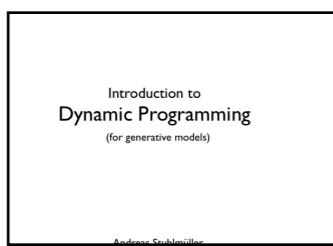


So-so

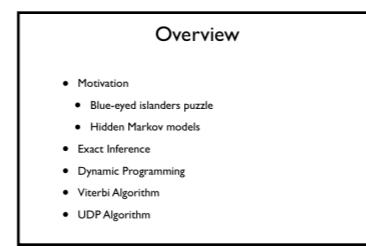
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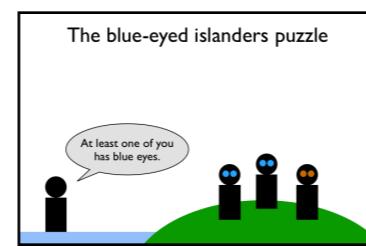
$$P(q_{1:n}) = P(q_n|q_{n-1}) \dots P(q_2|q_1) P_{init}(q_1)$$



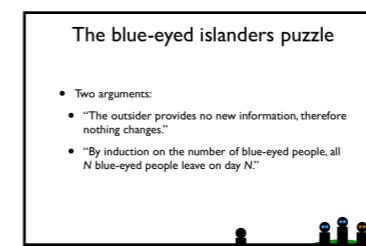
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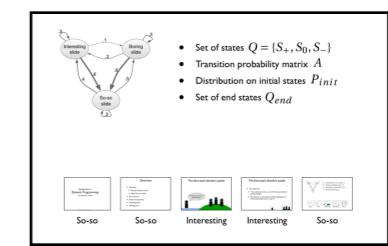
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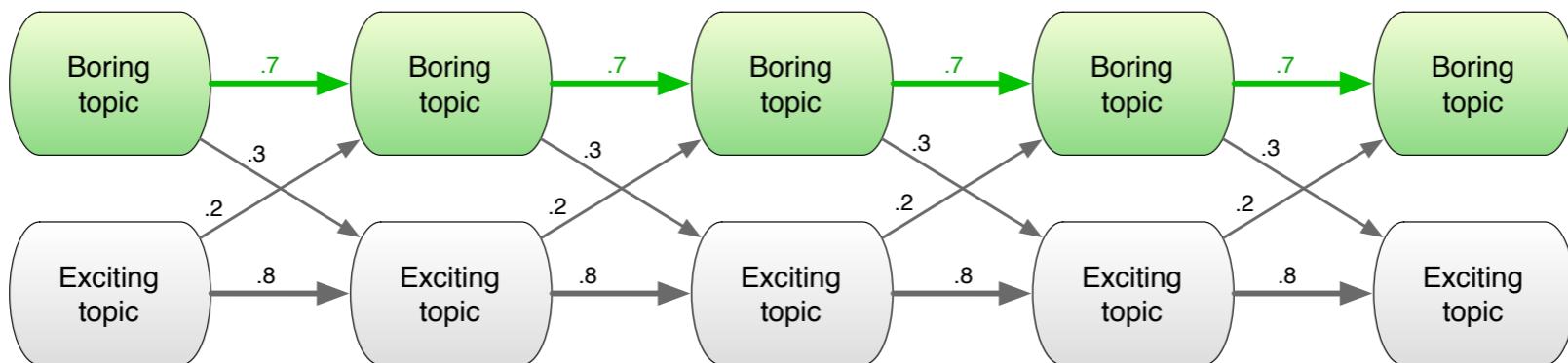


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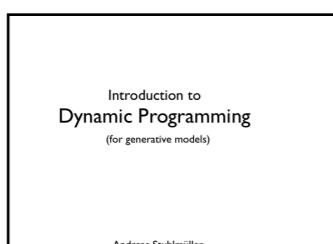
Inference by Enumeration



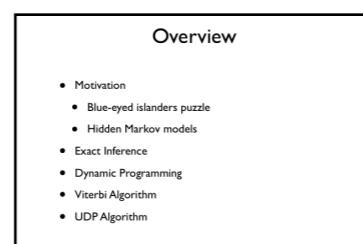
$$P(o_{1:n}|q_{1:n}) = P(o_n|q_n) \dots P(o_1|q_1)$$

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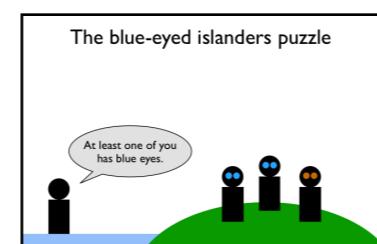
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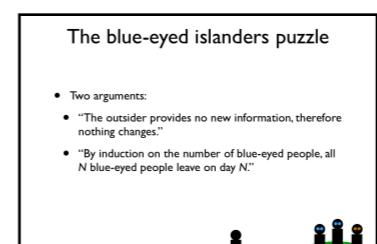
So-so



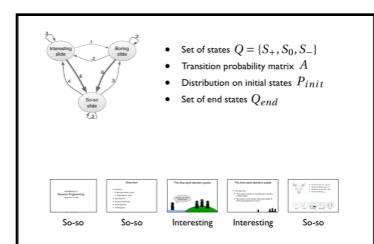
So-so



Interesting

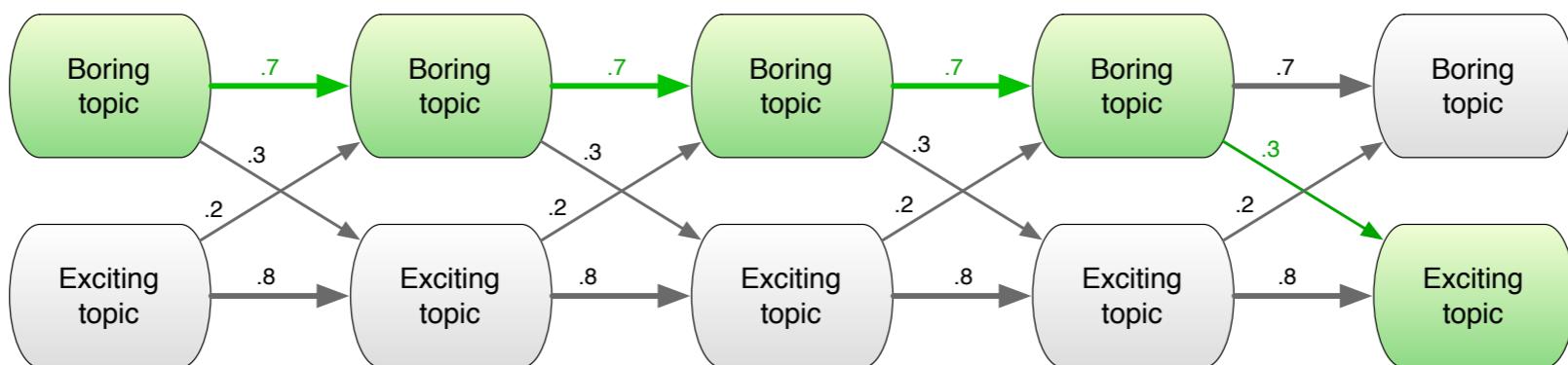


Interesting



So-so

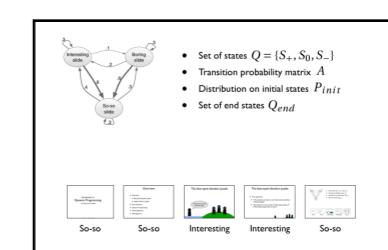
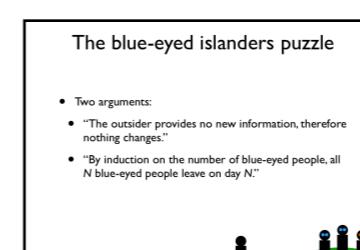
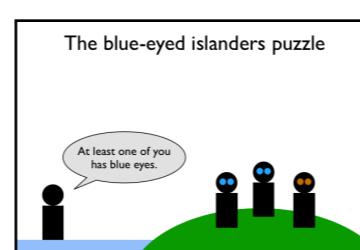
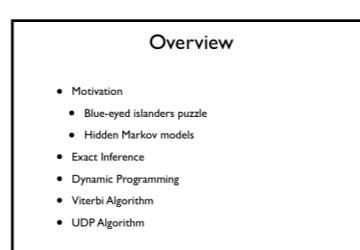
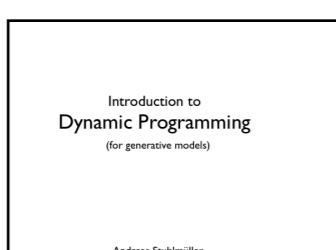
Inference by Enumeration



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So-so

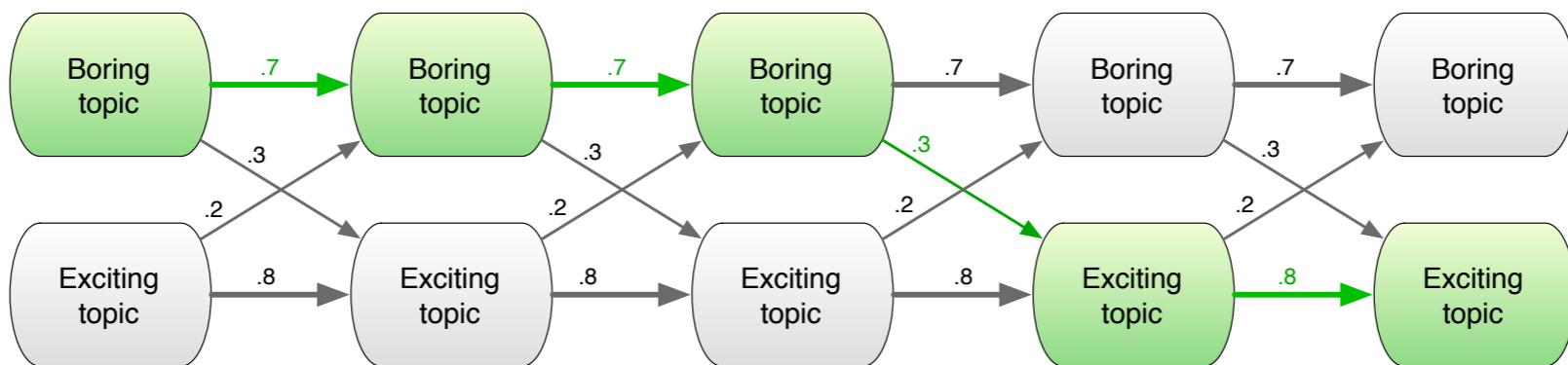
So-so

Interesting

Interesting

So-so

Inference by Enumeration



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Introduction to
Dynamic Programming
(for generative models)

Andreas Stuhlmüller

Overview

- Motivation
 - Blue-eyed islanders puzzle
 - Hidden Markov models
 - Exact Inference
 - Dynamic Programming
 - Viterbi Algorithm
 - UDP Algorithm

The blue-eyed islanders puzzle

At least one of you has blue eyes.

The blue-eyed islanders puzzle

- Two arguments:
 - "The outsider provides no new information, therefore nothing changes."
 - "By induction on the number of blue-eyed people, all N blue-eyed people leave on day N !"

- Set of states $Q = \{S_+, S_0, S_-\}$
- Transition probability matrix A
- Distribution on initial states P_{init}
- Set of end states Q_{end}

So-so

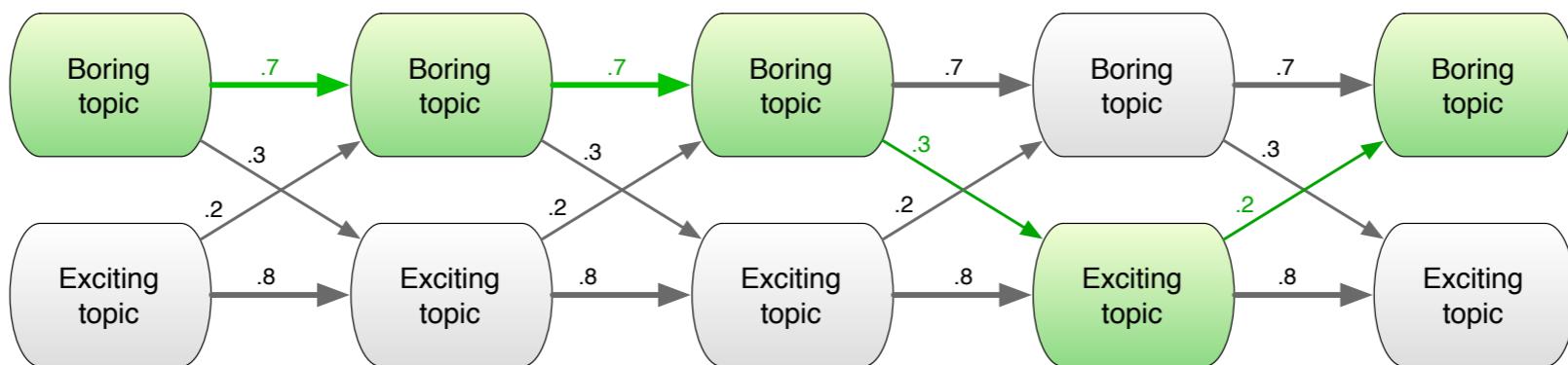
So-so

Interesting

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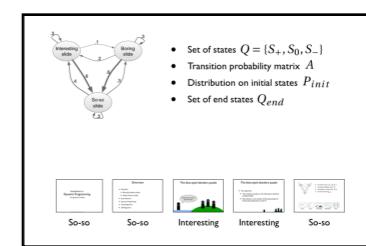
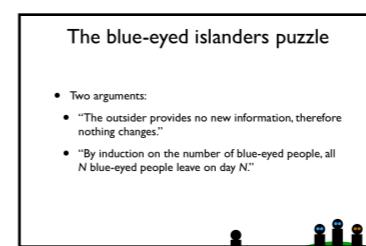
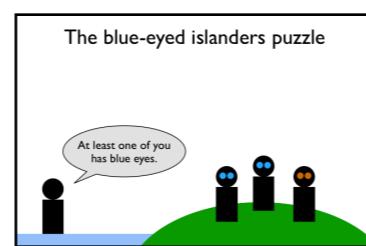
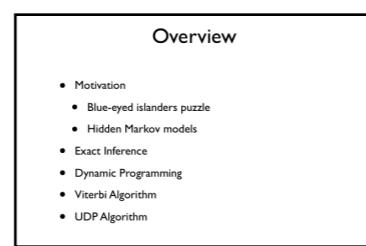
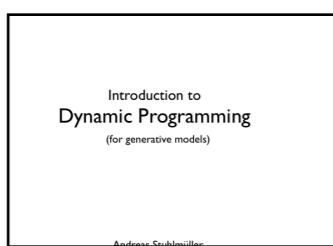
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So-so

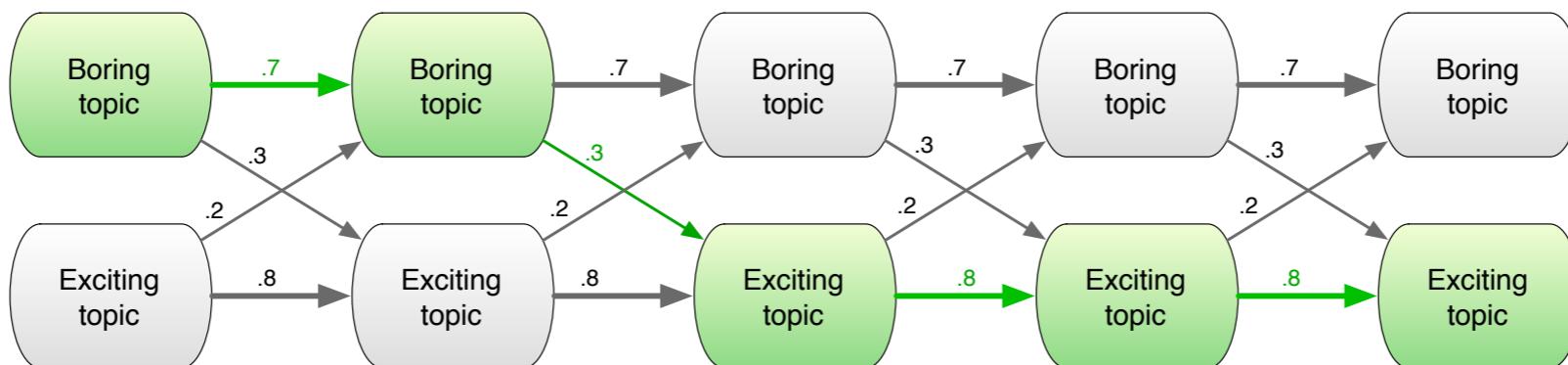
So-so

Interesting

Interesting

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Inference by Enumeration

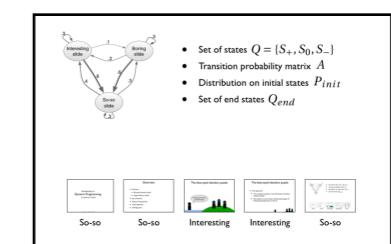
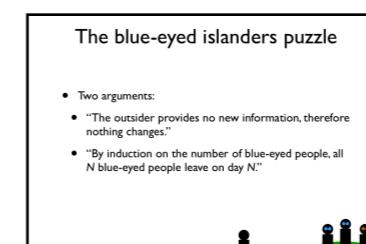
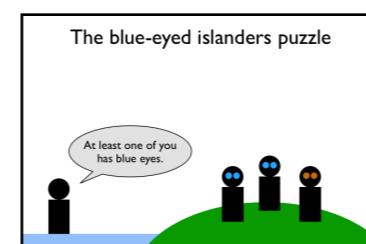
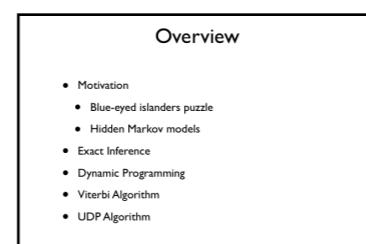
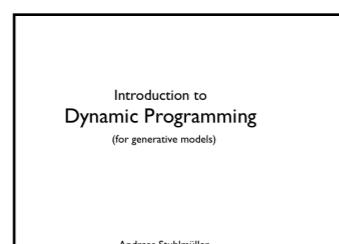


$|Q|^n$ paths

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So-so

So-so

Interesting

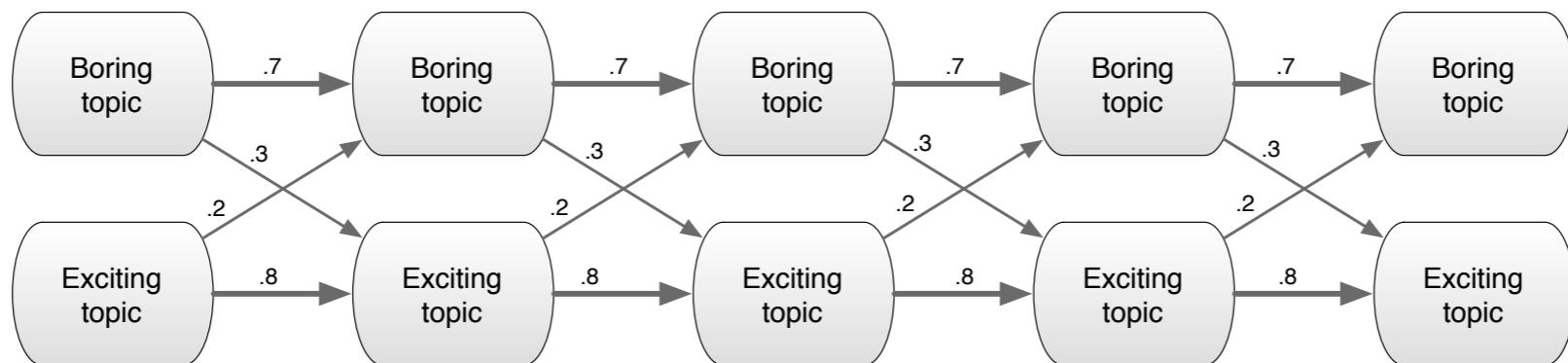
Interesting

So-so

Dynamic Programming

- Idea
 - Repeatedly reduce problem to smaller problems
 - Cache and reuse solutions to subproblems
- Requirements
 - Optimal substructure: Optimal solution to problem contains optimal solution to subproblems
 - Overlapping subproblems: Within solution to overall problem, need to solve subproblems multiple times

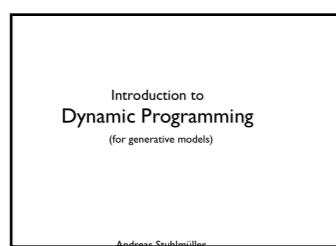
Forward Algorithm



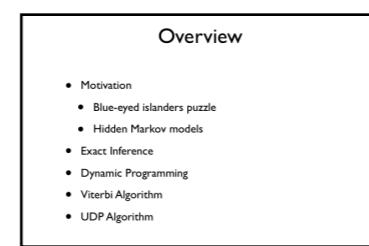
$$O(N|Q|^2)$$

$$P(o_{1:i}, q) = \begin{cases} P_{init}(q)P(o_1|q) & \text{if } i = 1 \\ \sum_{r \in Q} P(o_{1:(i-1)}, r)P(q|r)P(o_i|q) & \text{otherwise} \end{cases}$$

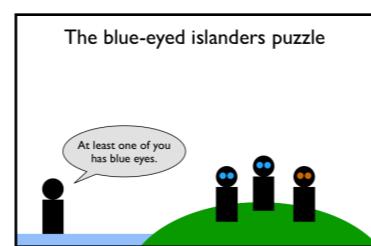
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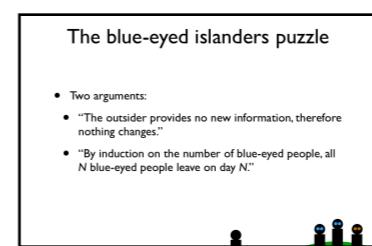
So-so



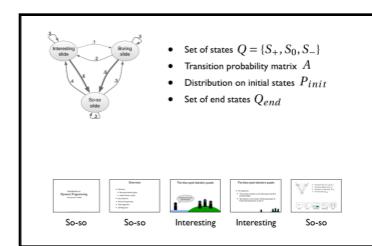
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Interesting

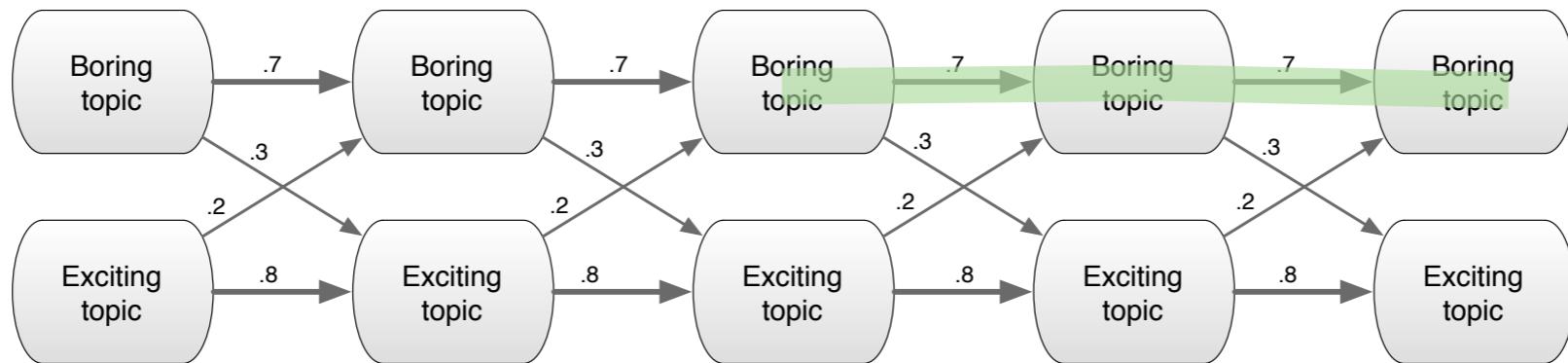


Interesting



So-so

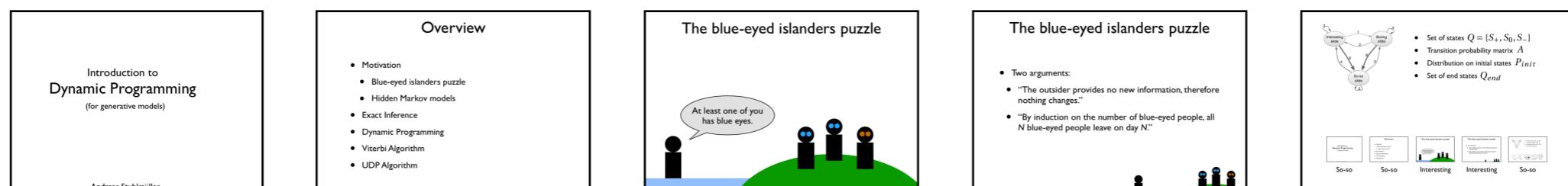
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So-so

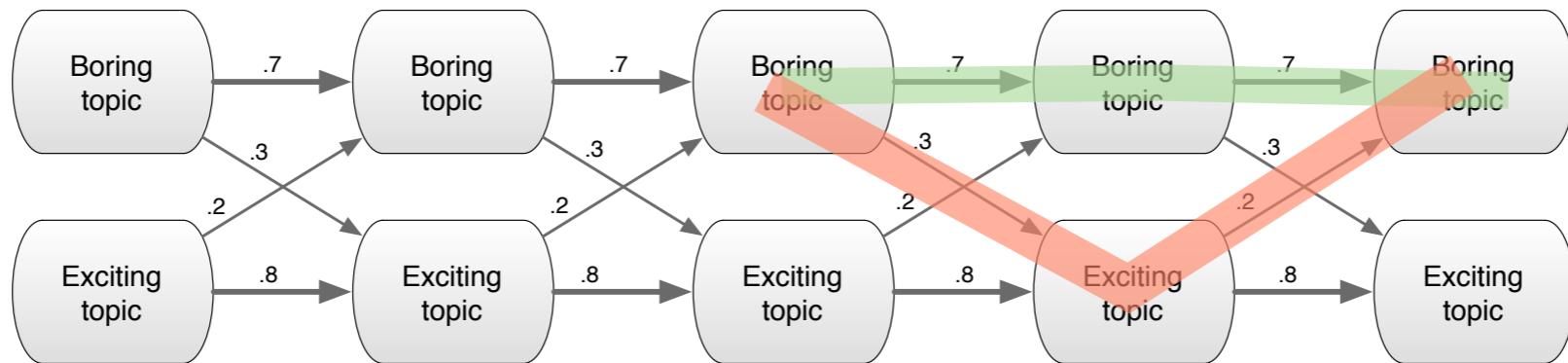
So-so

Interesting

Interesting

So-so

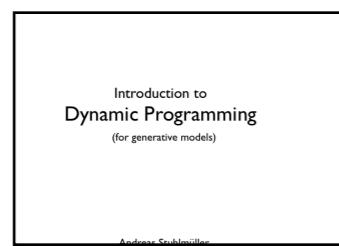
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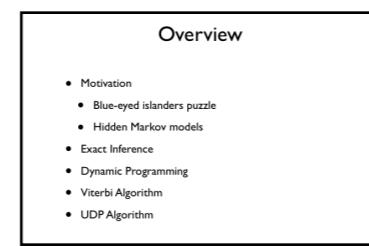
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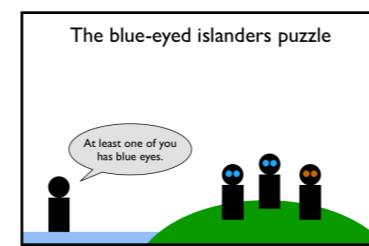
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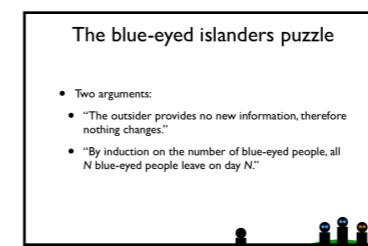
So-so



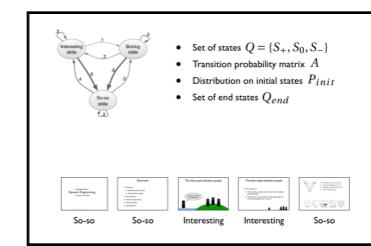
So-so



Interesting

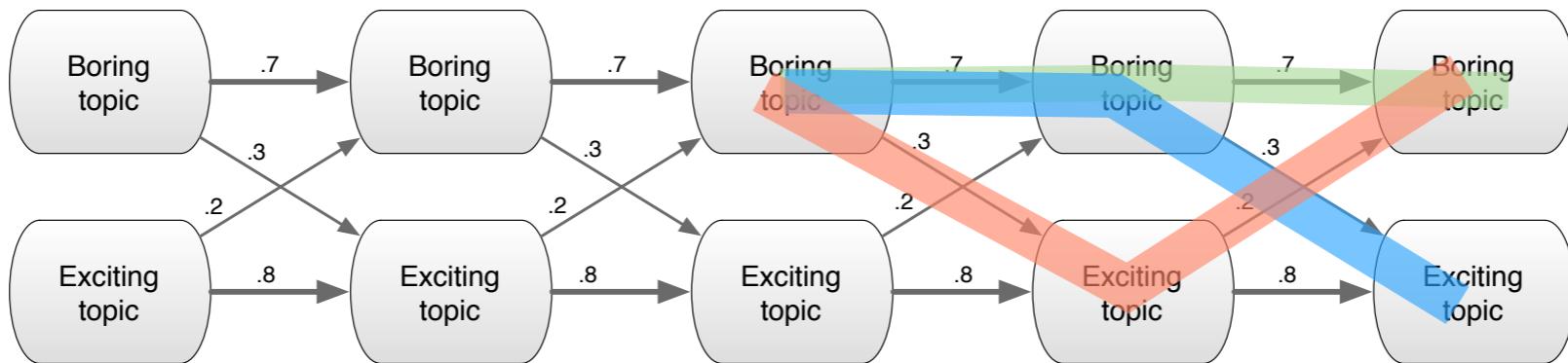


Interesting



So-so

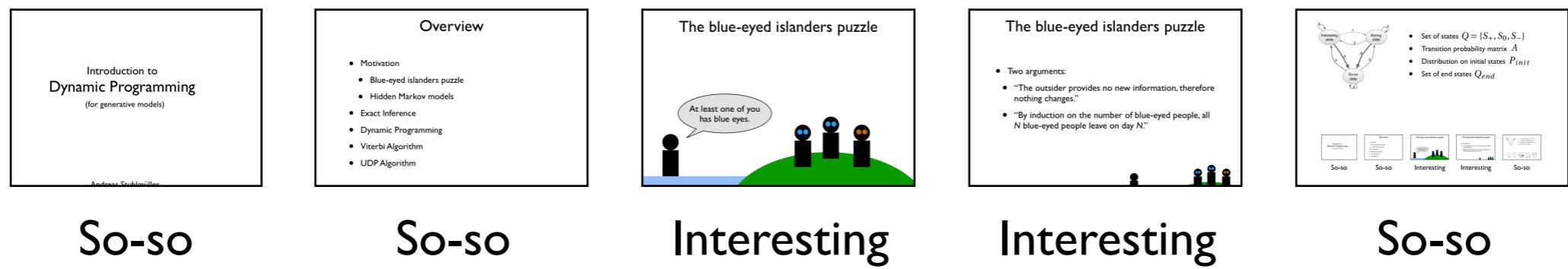
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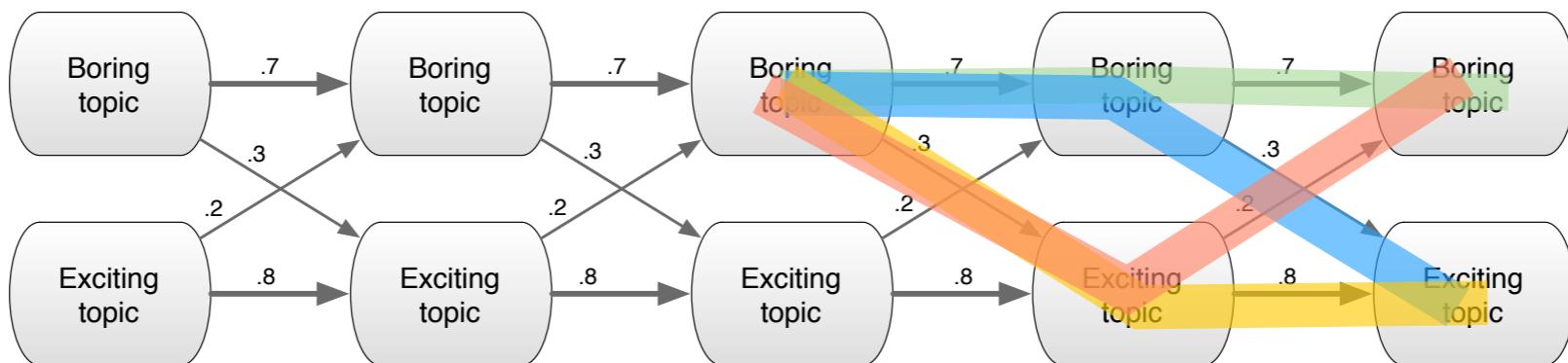
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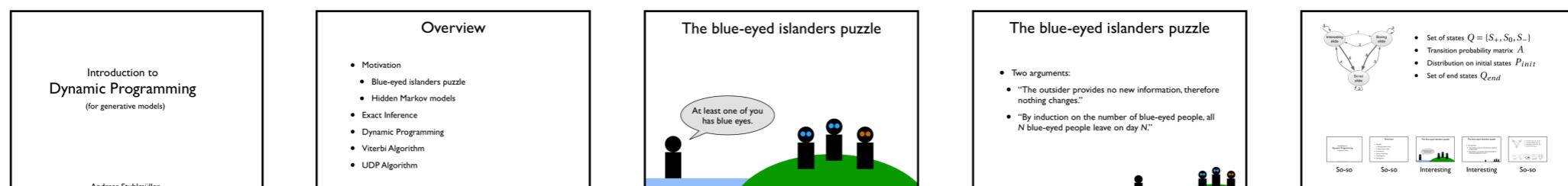
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So-so

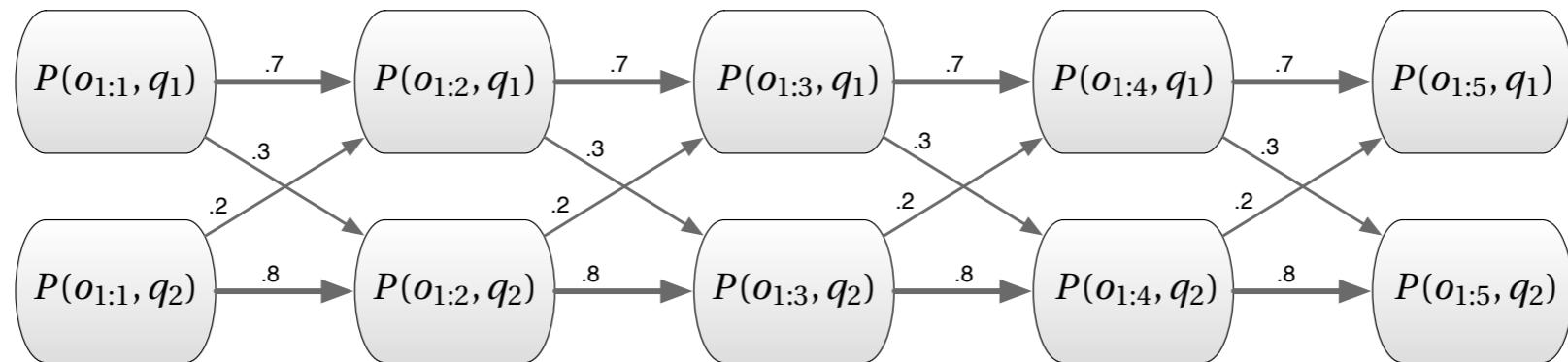
So-so

Interesting

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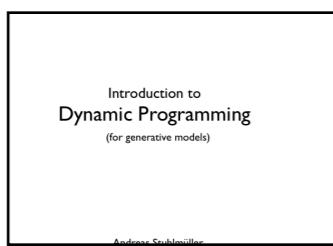
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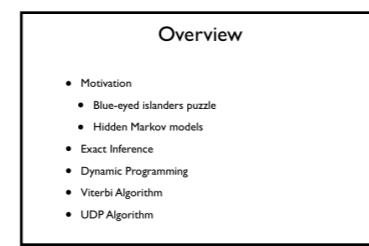
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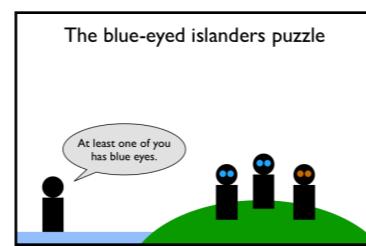
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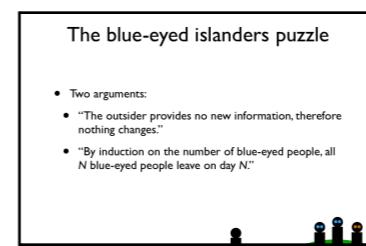
So-so



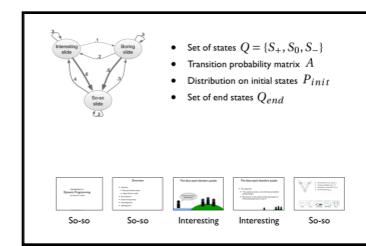
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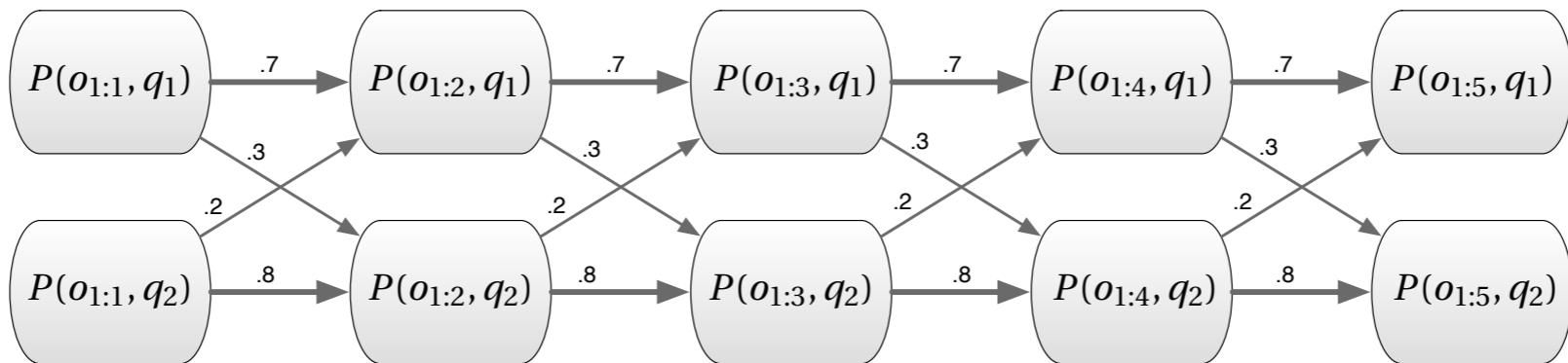


Interesting



So-so

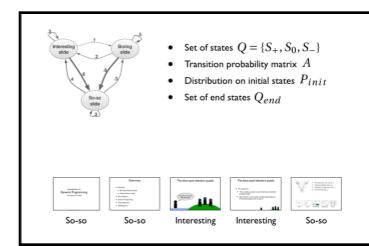
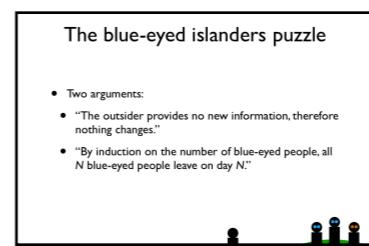
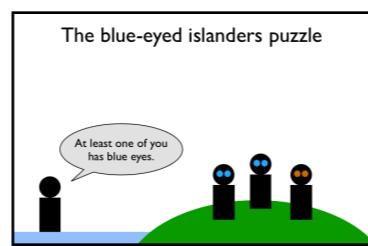
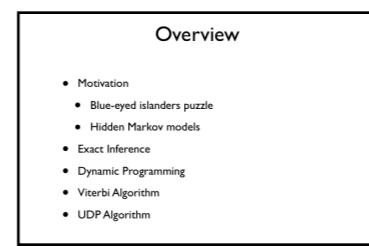
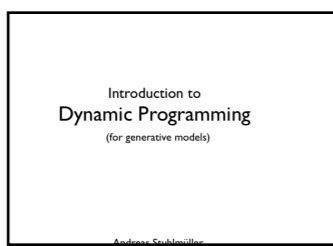
Viterbi Algorithm



$$O(N|Q|^2)$$

$$P_{max}(o_{1:i}, q) = \begin{cases} P_{init}(q)P(o_1|q) & \text{if } i = 1 \\ \max_{r \in Q} P_{max}(o_{1:(i-1)}, r)P(q|r)P(o_i|q) & \text{otherwise} \end{cases}$$

$$P_{max}(o_{1:i}) = \max_{q \in Q} P_{max}(o_{1:i}, q)$$



So-so

So-so

Interesting

Interesting

So-so

Dynamic Programming Algorithms

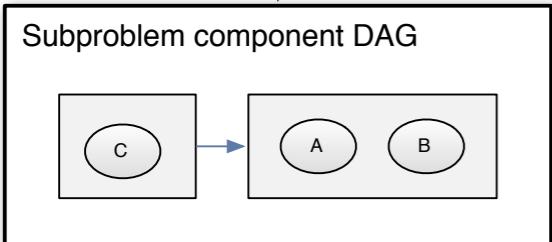
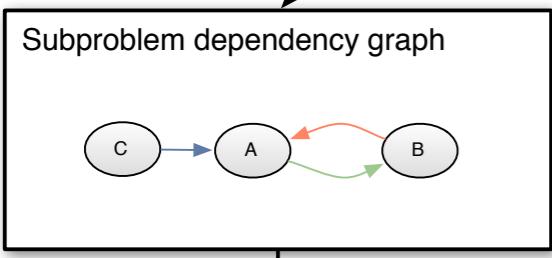
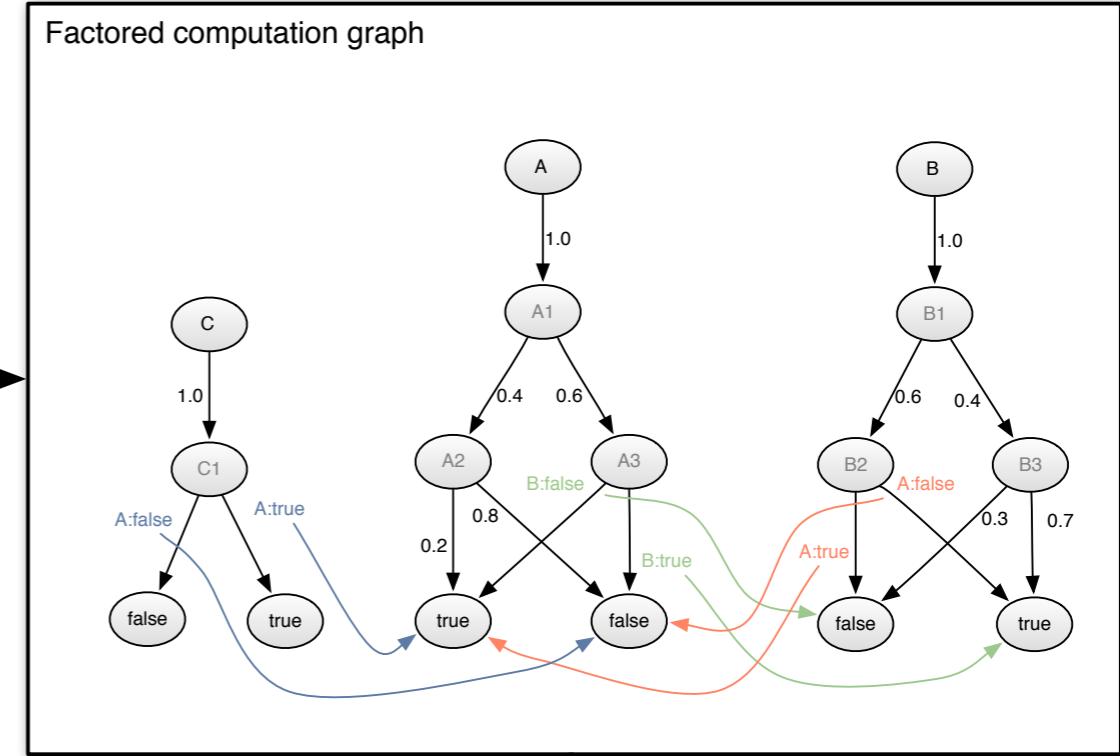
- Many DP algorithms exist ...
 - HMMs: Forward, Viterbi, Forward-Backward
 - PCFGs: Earley, CYK
 - MDPs: Bellman backups
- ... but probabilistic programming allows us to write many more models without known solutions
- Goal: Universal DP to make inference in some of these models tractable

Original program

```
(define (game player)
  (if (flip .6)
      (not (game (not player)))
      (if player
          (flip .2)
          (flip .7))))
  (game true))
```

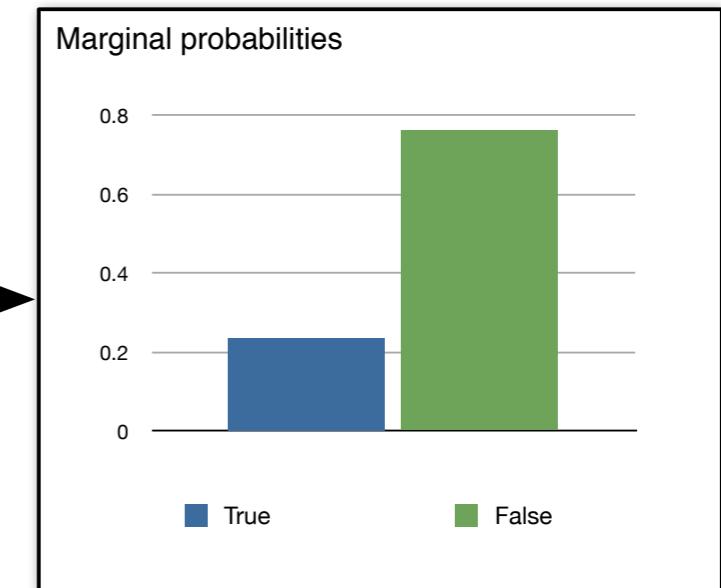
Transformed program

```
...((vector-ref op265 0) op265
  (vector
    (lambda (self266 tmp151)
      (let ((b135 tmp151))
        (let ((op267
              (vector-ref
                self266 2)))
          ((vector-ref op267 0)
            op267
            (vector
              (lambda
                (self268 tmp153)
                (make-application
                  tmp153
                  (vector-ref
                    self268 2)
                  #t))
              '60
              (vector-ref
                self266 3))
              (vector-ref
                self266
                4))))
        '61 (vector-ref self258 3)
        k134 game)
        game abs136)
  ...)
```



Systems of polynomial equations

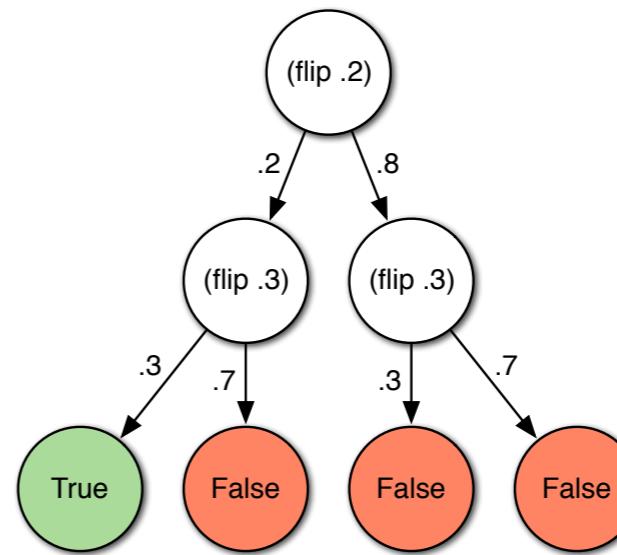
$C1 = 1.0 * C$	$A1 = 1.0 * A$
$C:\text{false} = \boxed{A:\text{false}} * C1$	$A2 = 0.4 * A1$
$C:\text{true} = \boxed{A:\text{true}} * C1$	$A3 = 0.6 * A1$
	$\boxed{A:\text{false}} = 0.8 * A2 + \boxed{B:\text{true}} * A3$
	$\boxed{A:\text{true}} = 0.2 * A2 + \boxed{B:\text{false}} * A3$
	$B1 = 1.0 * B$
	$B2 = 0.6 * B1$
	$B3 = 0.4 * B1$
	$\boxed{B:\text{false}} = 0.3 * B3 + \boxed{A:\text{true}} * B2$
	$\boxed{B:\text{true}} = 0.7 * B3 + \boxed{A:\text{false}} * B2$



DP for probabilistic programs

- Enumeration

```
(define (foo)
  (and (flip .2)
       (flip .3)))  
  
(foo)
```



- Factorization
- State merging
- Challenge: Recursive non-tail dependencies

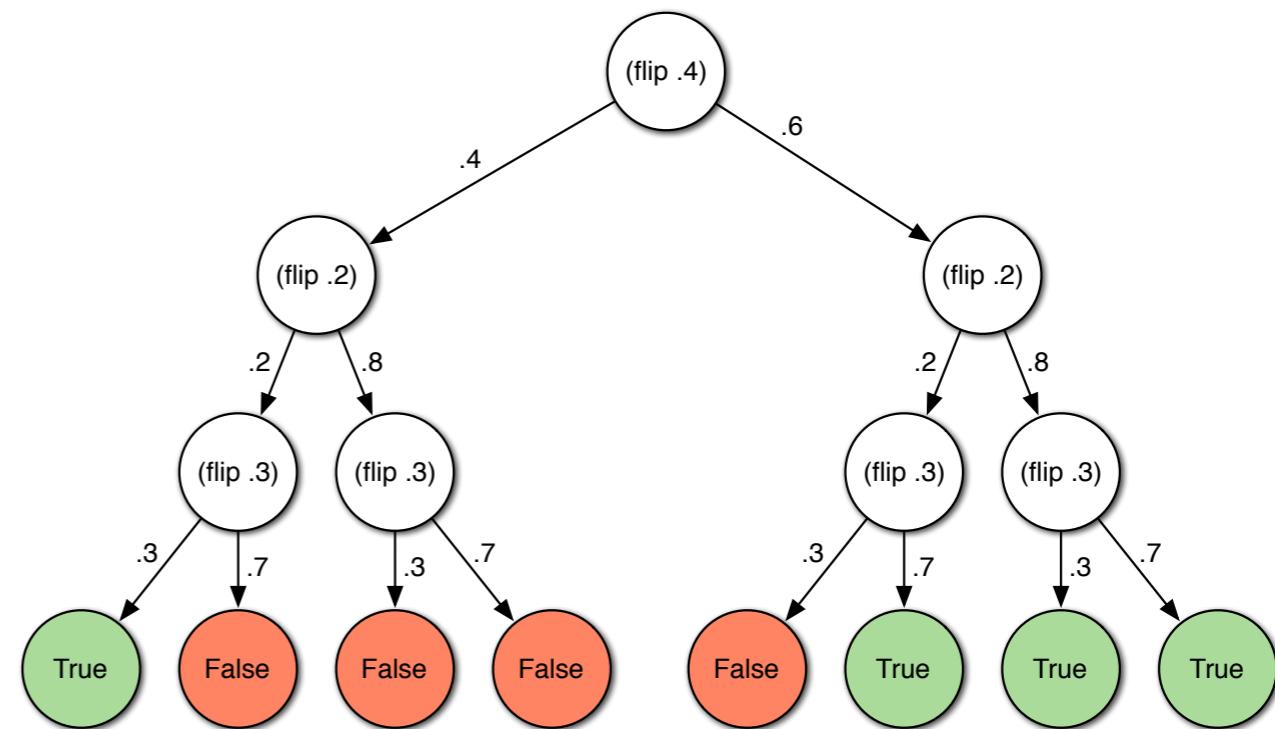
DP for probabilistic programs

- Enumeration
- Factorization

```
(define (outer)
  (if (flip .4)
      (inner)
      (not (inner))))
```

```
(define (inner)
  (and (flip .2)
       (flip .3)))
```

(outer)



- State merging
- Challenge: Recursive non-tail dependencies

DP for probabilistic programs

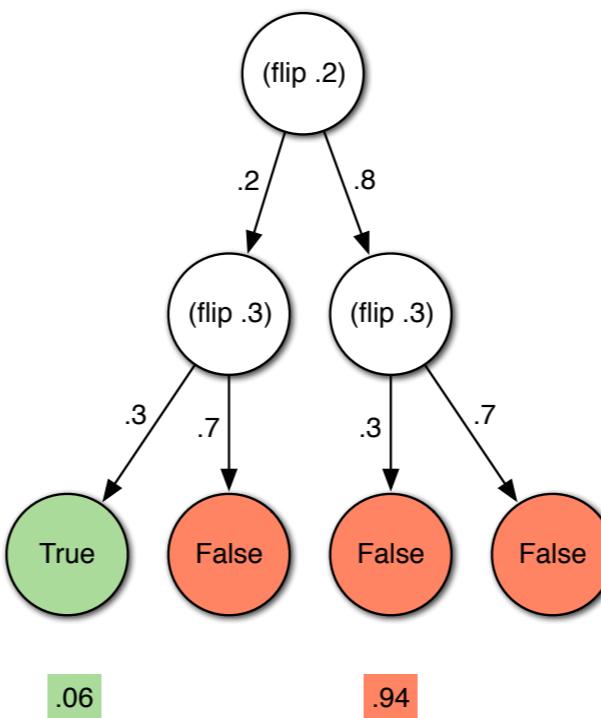
- Enumeration
- Factorization

```
(define (outer)
  (if (flip .4)
      (inner)
      (not (inner))))
```

```
(define (inner)
  (and (flip .2)
       (flip .3)))
```

(outer)

(inner)



- State merging
- Challenge: Recursive non-tail dependencies

DP for probabilistic programs

- Enumeration
- Factorization

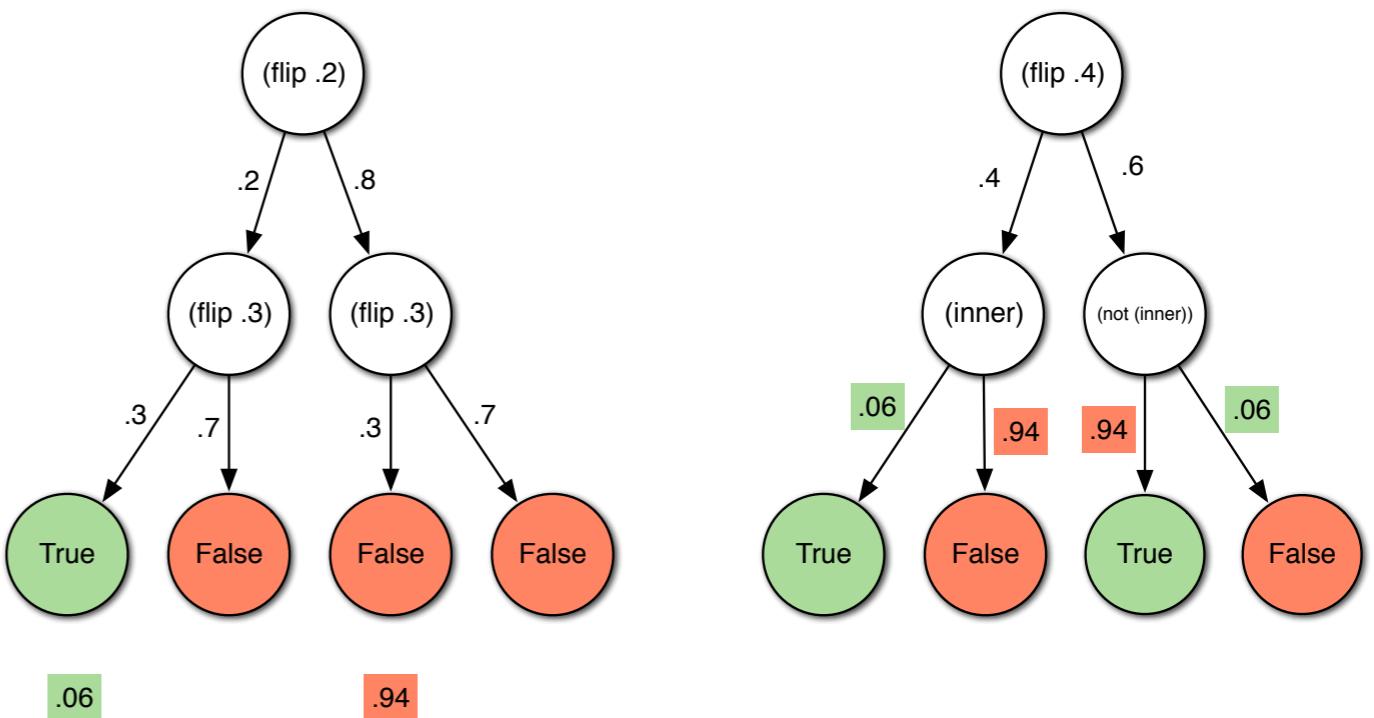
```
(define (outer)
  (if (flip .4)
      (inner)
      (not (inner))))
```

```
(define (inner)
  (and (flip .2)
       (flip .3)))
```

(outer)

(inner)

(outer)

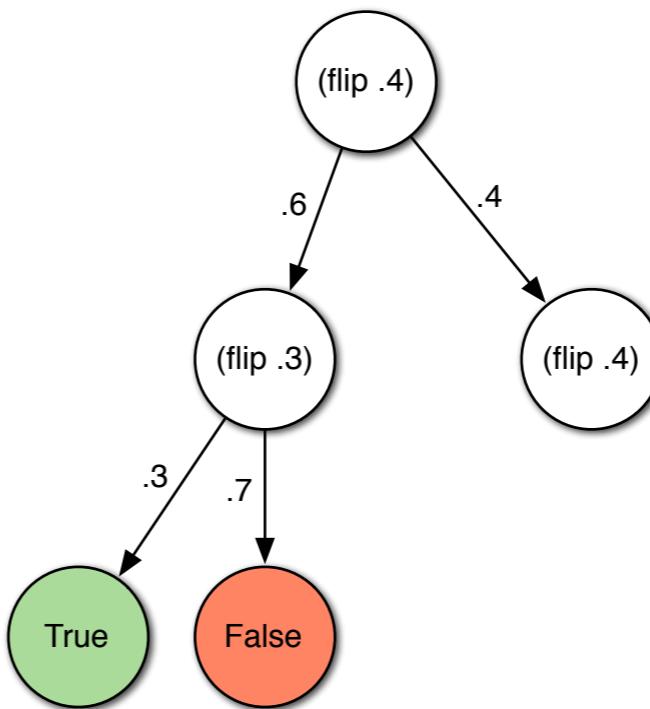


- State merging
- Challenge: Recursive non-tail dependencies

DP for probabilistic programs

- Enumeration
- Factorization
- State merging

```
(define (tail)
  (if (flip .4)
      (tail)
      (flip .3)))
(tail)
```



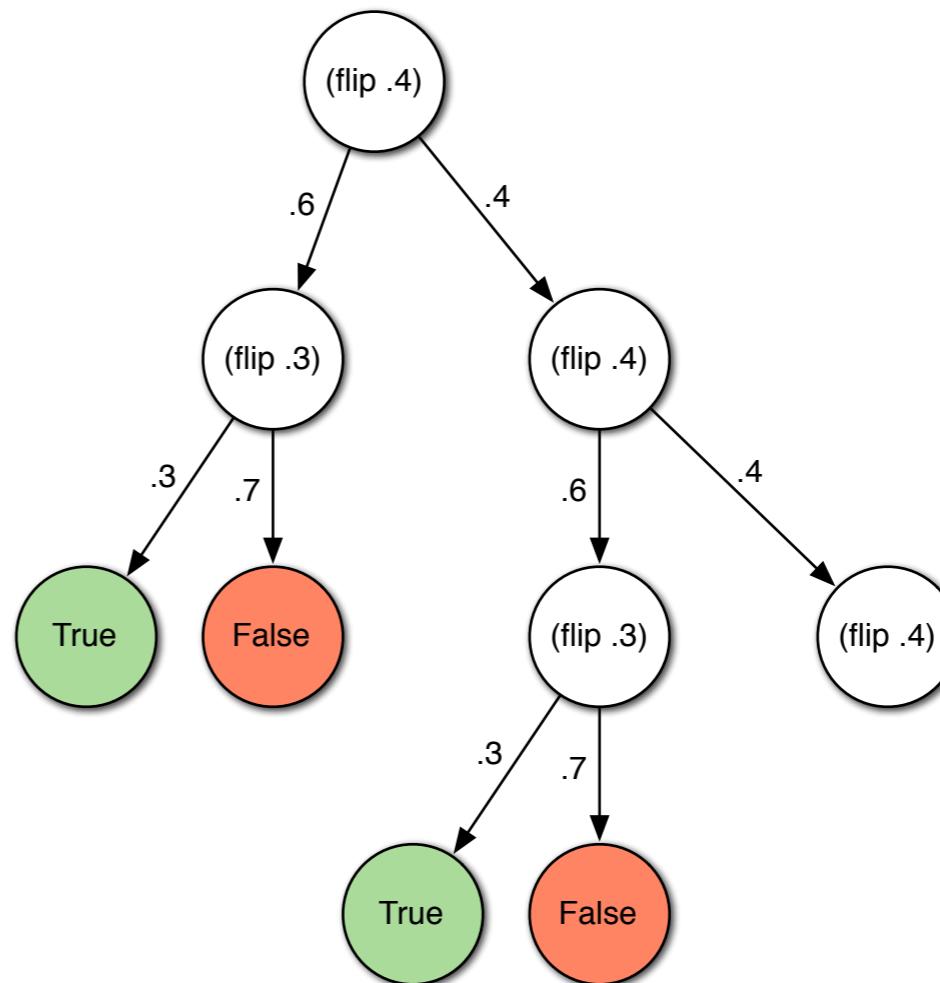
- Challenge: Recursive non-tail dependencies

DP for probabilistic programs

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(define (tail)
  (if (flip .4)
      (tail)
      (flip .3)))
```

(tail)



- Challenge: Recursive non-tail dependencies

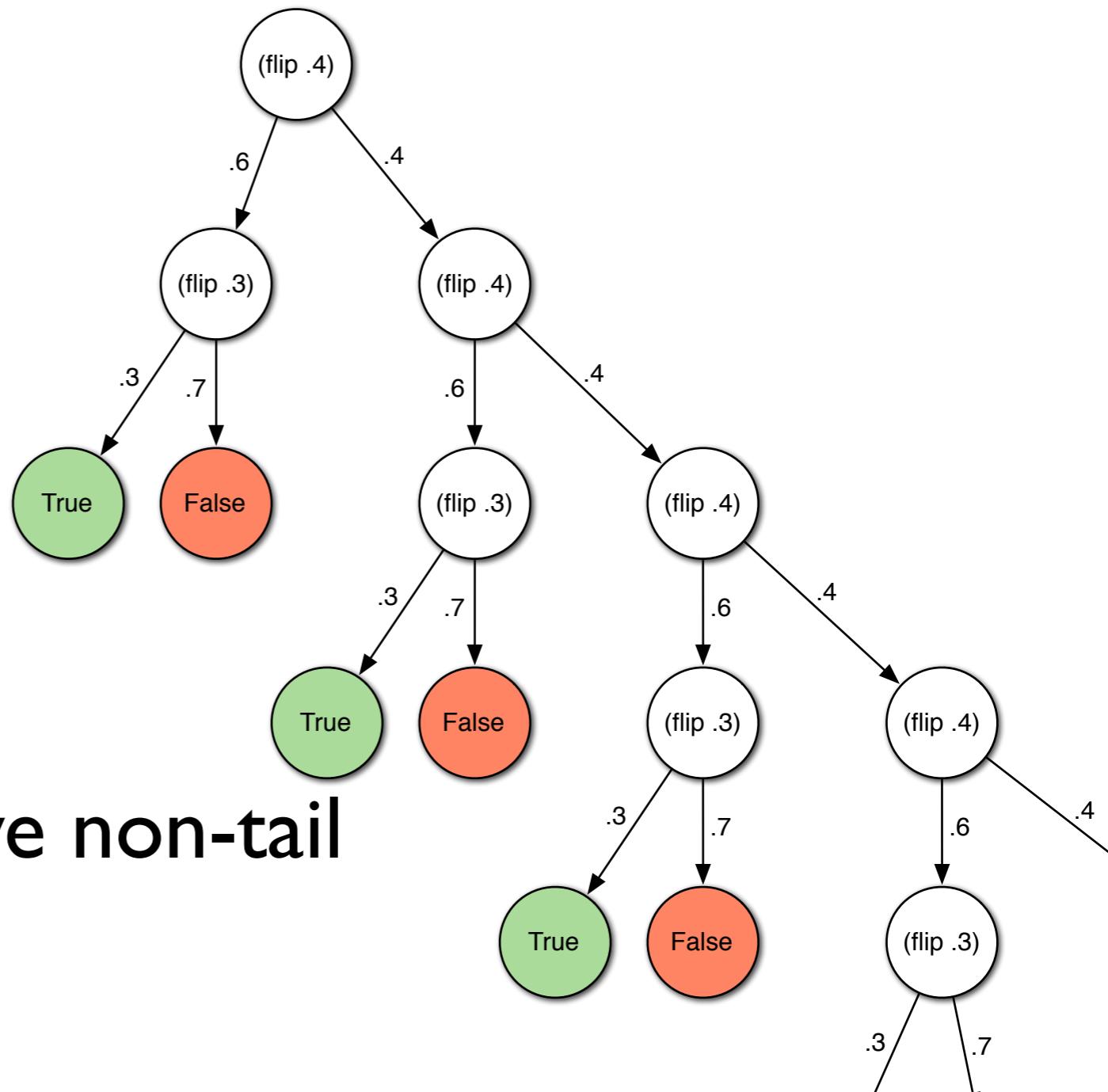
DP for probabilistic programs

- Enumeration
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```
(define (tail)
  (if (flip .4)
      (tail)
      (flip .3)))
```

(tail)

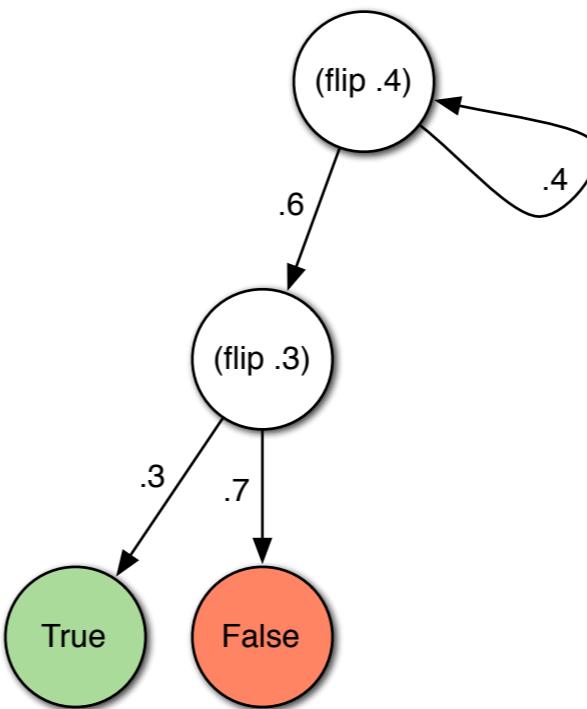
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DP for probabilistic programs

- Enumeration
- Factorization
- State merging

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(define (tail)
  (if (flip .4)
      (tail)
      (flip .3)))
(tail)
```

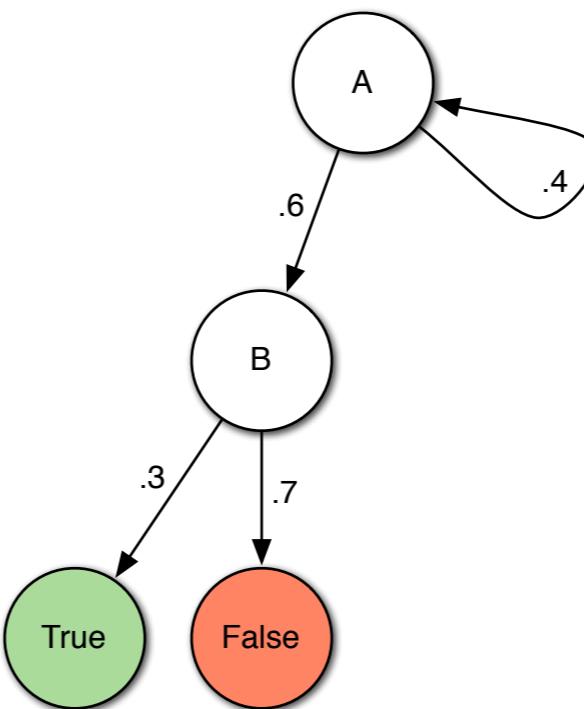


- Challenge: Recursive non-tail dependencies

DP for probabilistic programs

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- State merging

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(define (tail)
  (if (flip .4)
      (tail)
      (flip .3)))
(tail)
```

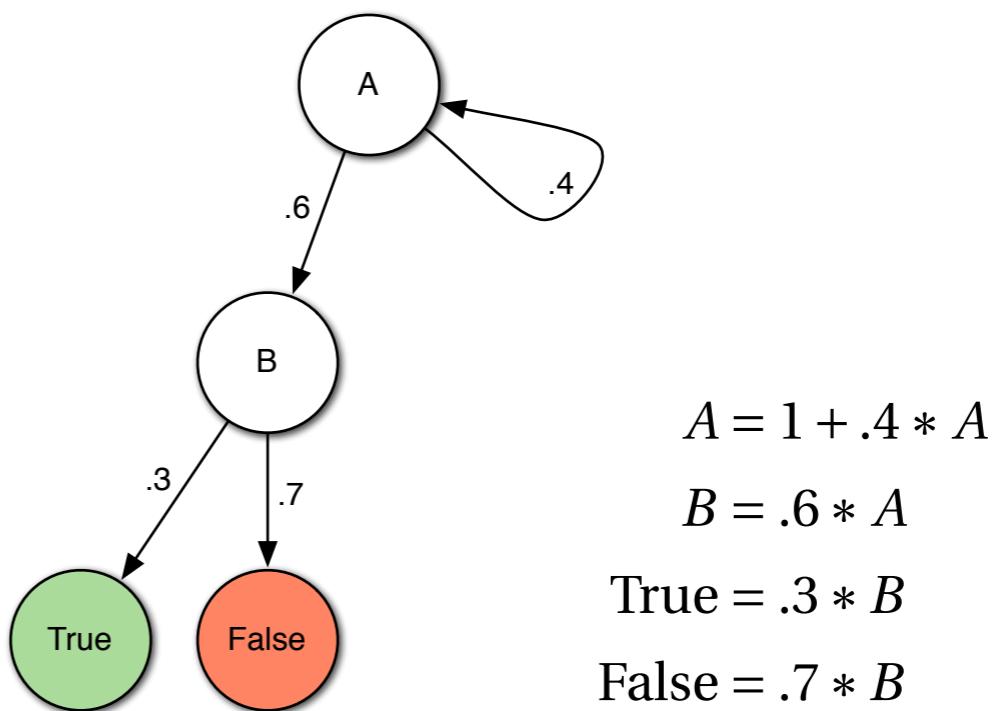


- Challenge: Recursive non-tail dependencies

DP for probabilistic programs

- Enumeration
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- State merging

```
(define (tail)
  (if (flip .4)
      (tail)
      (flip .3)))
(tail)
```



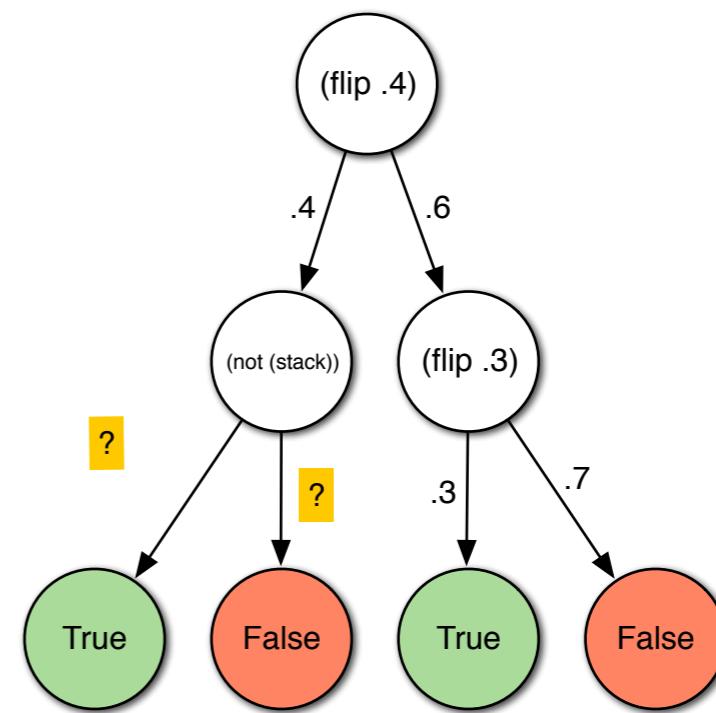
- Challenge: Recursive non-tail dependencies

Challenge: Recursive dependencies

```
(define (stack)
  (if (flip .4)
      (not (stack))
      (flip .3)))
```

(stack)

(stack)

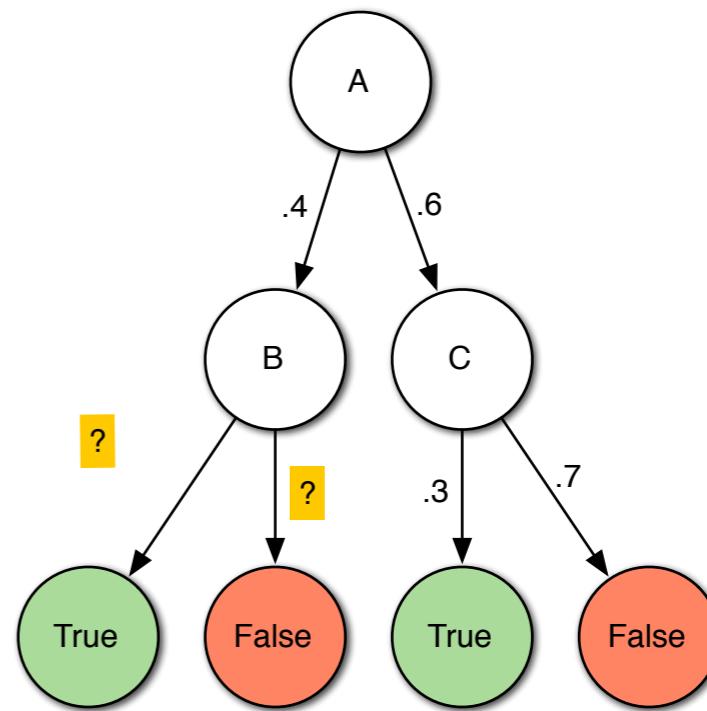


Challenge: Recursive dependencies

```
(define (stack)
  (if (flip .4)
      (not (stack))
      (flip .3)))
```

(stack)

(stack)

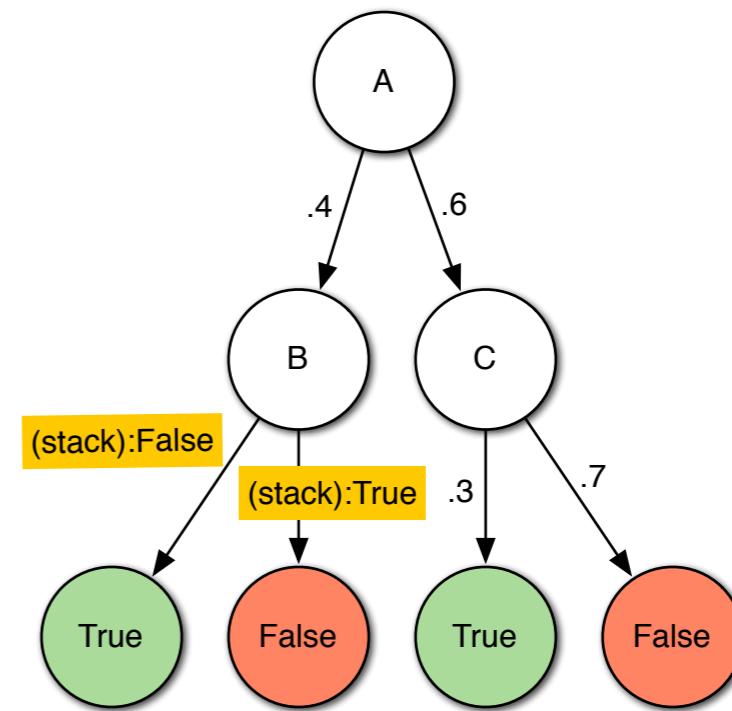


Challenge: Recursive dependencies

```
(define (stack)
  (if (flip .4)
      (not (stack))
      (flip .3)))
```

(stack)

(stack)



Challenge: Recursive dependencies

```
(define (stack)
  (if (flip .4)
      (not (stack))
      (flip .3)))
```

(stack)

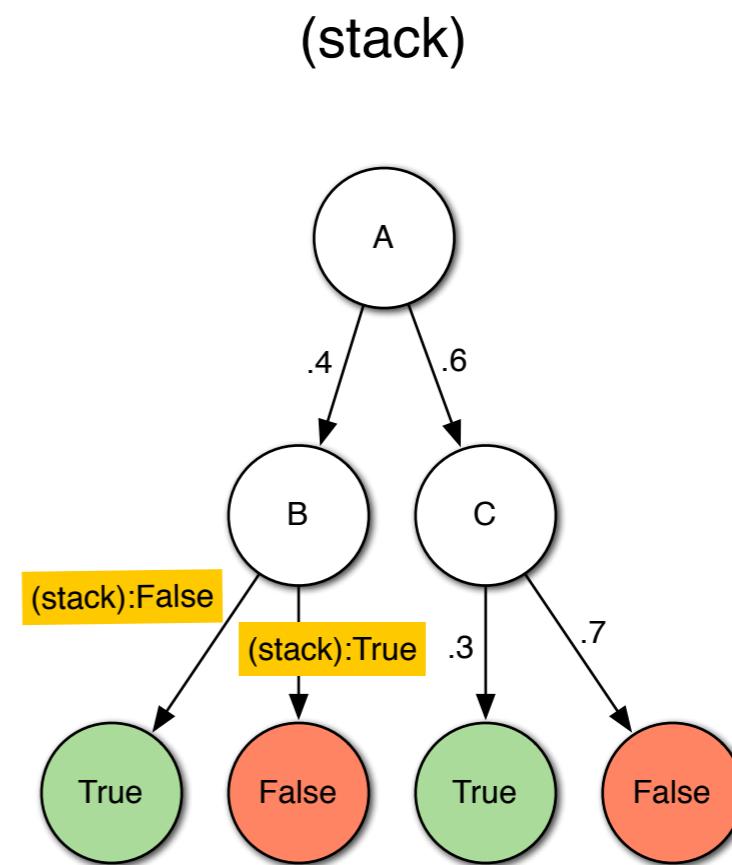
$$A = 1$$

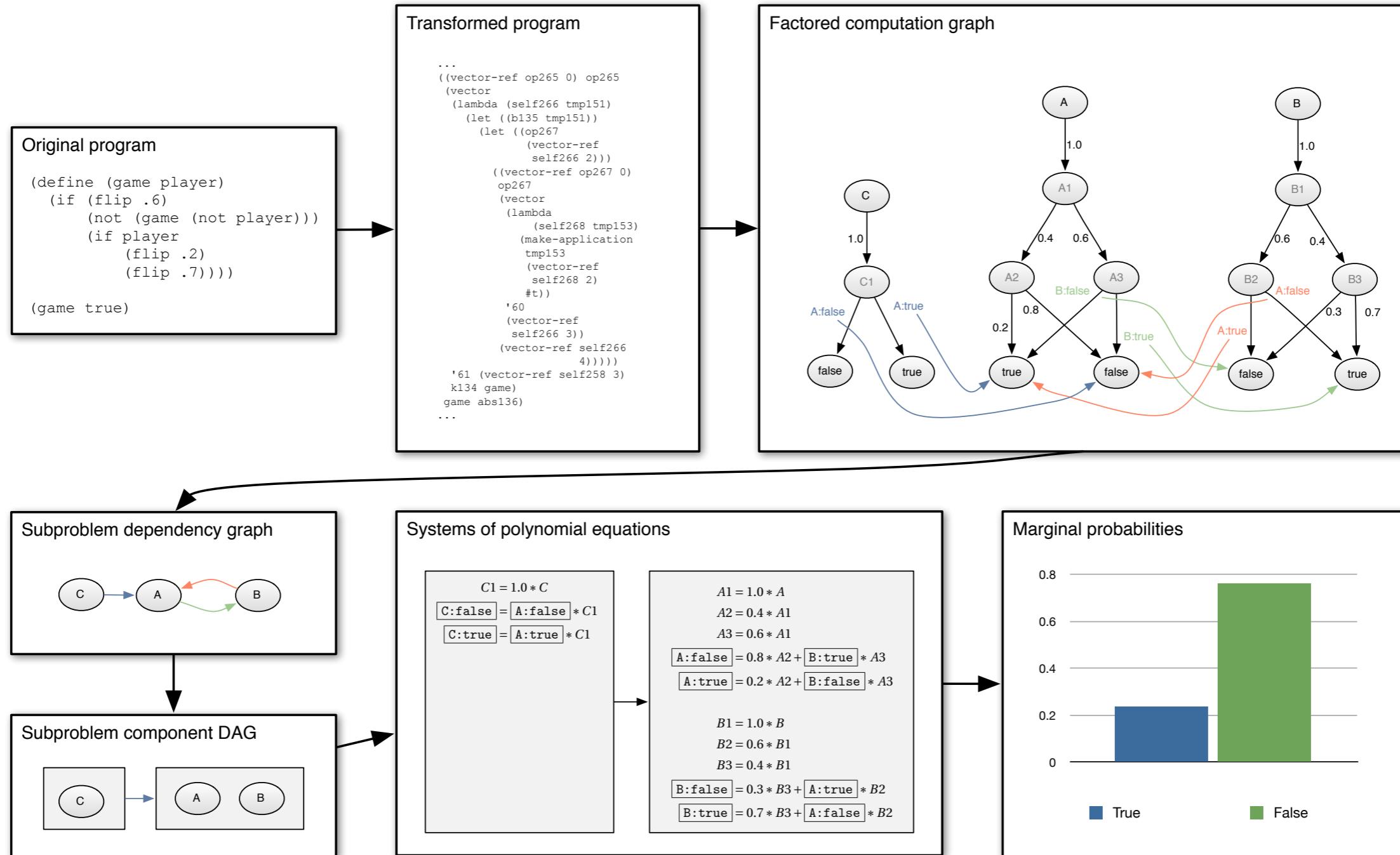
$$B = .4 * A$$

$$C = .6 * A$$

$$(\text{stack}) : \text{True} = (\text{stack}) : \text{False} * B + .3 * C$$

$$(\text{stack}) : \text{False} = (\text{stack}) : \text{True} * B + .7 * C$$





Transformed program

```
...
((vector-ref op265 0) op265
 (vector
  (lambda (self266 tmp151)
    (let ((b135 tmp151))
      (let ((op267
             (vector-ref
              self266 2)))
        ((vector-ref op267 0)
         op267
         (vector
          (lambda
           (self268 tmp153)
           (make-application
            tmp153
            (vector-ref
              self268 2)
            #t)))
         '60
         (vector-ref
          self266 3))
        (vector-ref self266
          4))))))
 '61 (vector-ref self258 3)
 k134 game)
 game abs136)
 ...
...
```

Original program

```
(define (game player)
  (if (flip .6)
      (not (game (not player))))
  (if player
      (flip .2)
      (flip .7)))))

(game true)
```

Subproblem dependency graph



Systems of polynomial equations

$$C1 = 1.0 * C$$

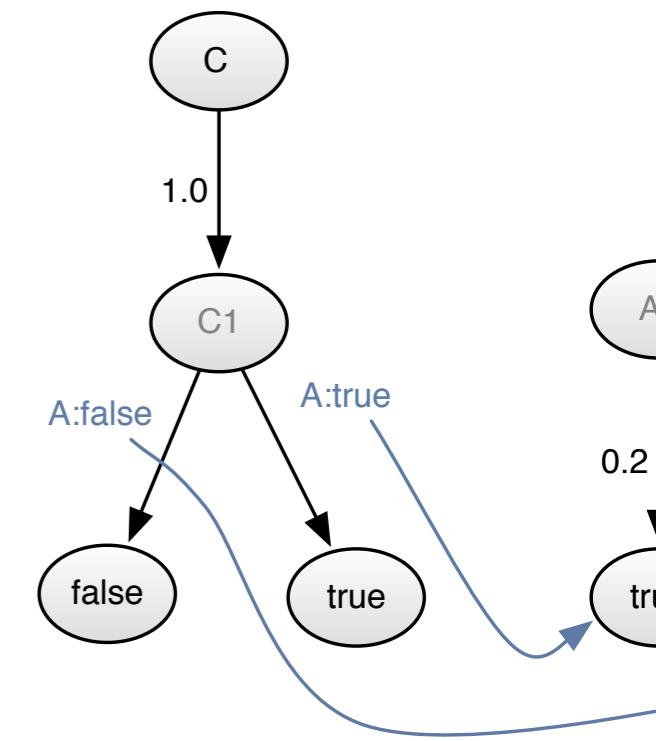
program

```
game player)
ip .6)
t (game (not player)))
player
(flip .2)
(flip .7)) )
e)
```

Transformed program

```
...
((vector-ref op265 0) op265
 (vector
  (lambda (self266 tmp151)
    (let ((b135 tmp151))
      (let ((op267
            (vector-ref
             self266 2)))
        ((vector-ref op267 0)
         op267
         (vector
          (lambda
           (self268 tmp153)
           (make-application
            tmp153
            (vector-ref
             self268 2)
             #t))
          '60
          (vector-ref
           self266 3))
         (vector-ref self266
                    4))))))
 '61 (vector-ref self258 3)
 k134 game)
game abs136)
...
```

Factored computation graph



dependency graph

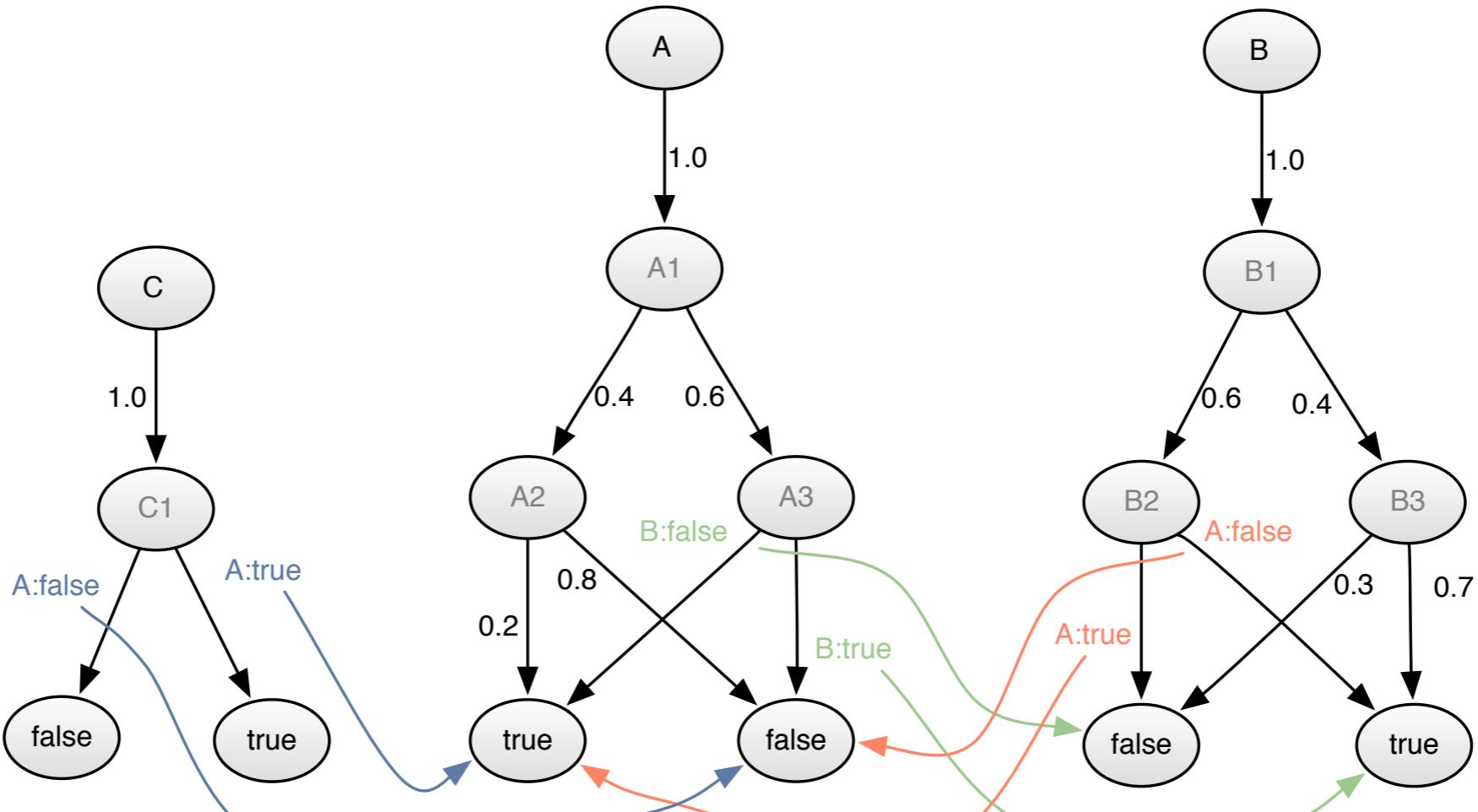


Systems of polynomial equations

$$C_1 = 1.0 * C$$

$$A_1 = 1.0 * A$$

Factored computation graph



0)
53)
on

6)
)

iations

$$A1 = 1.0 * A$$

Marginal probabilities

0.8

```
'61 (vector-ref self258 3)  
k134 game)  
game abs136)  
...
```

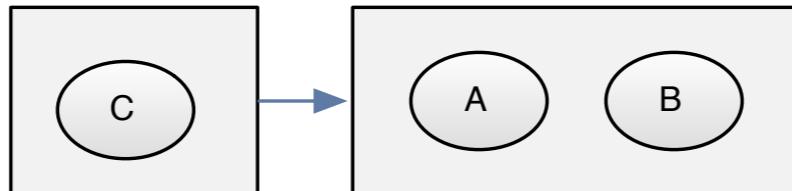
Subproblem dependency graph



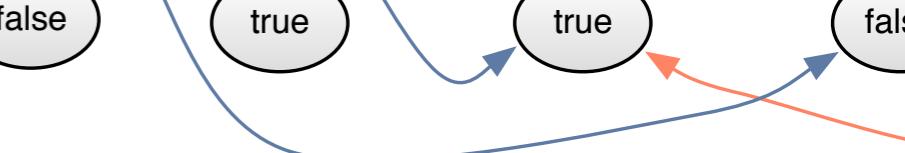
Systems of polynomial equations

$$C1 = 1.0 * C$$
$$C:\text{false} = A:\text{false} * C1$$
$$C:\text{true} = A:\text{true} * C1$$

Subproblem component DAG



```
'61 (vector-ref self258 3)  
k134 game  
game abs136  
...
```



/ graph

DAG

B

Systems of polynomial equations

$$C1 = 1.0 * C$$

$$C:\text{false} = \boxed{A:\text{false}} * C1$$

$$C:\text{true} = \boxed{A:\text{true}} * C1$$

$$A1 = 1.0 * A$$

$$A2 = 0.4 * A1$$

$$A3 = 0.6 * A1$$

$$\boxed{A:\text{false}} = 0.8 * A2 + \boxed{B:\text{true}} * A3$$

$$\boxed{A:\text{true}} = 0.2 * A2 + \boxed{B:\text{false}} * A3$$

$$B1 = 1.0 * B$$

$$B2 = 0.6 * B1$$

$$B3 = 0.4 * B1$$

$$\boxed{B:\text{false}} = 0.3 * B3 + \boxed{A:\text{true}} * B2$$

$$\boxed{B:\text{true}} = 0.7 * B3 + \boxed{A:\text{false}} * B2$$

Marginal prob

0.8

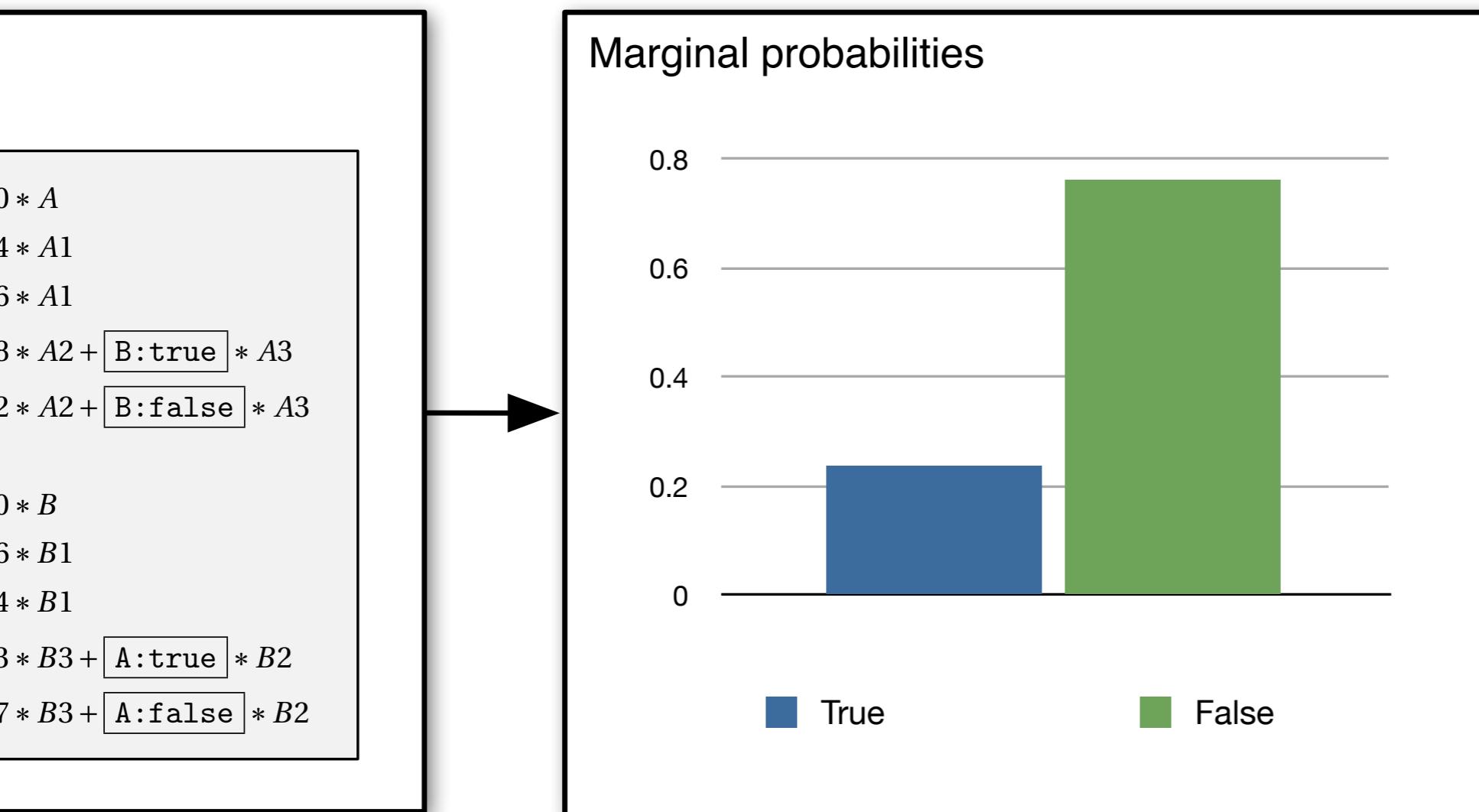
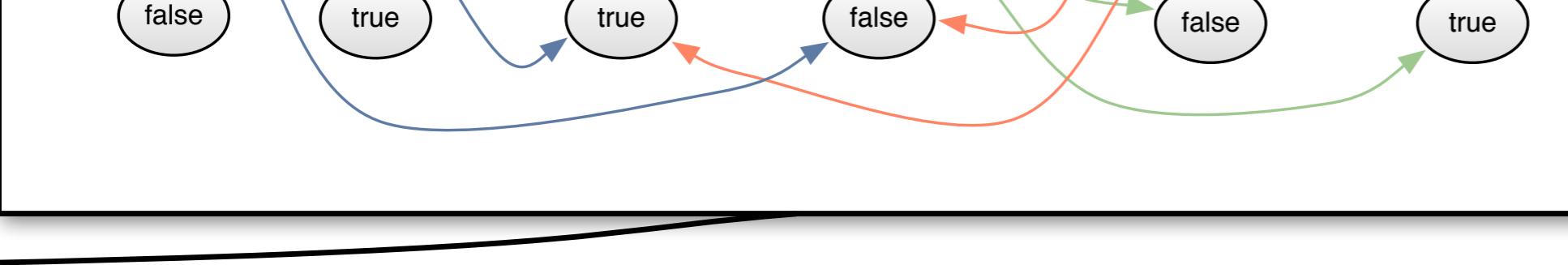
0.6

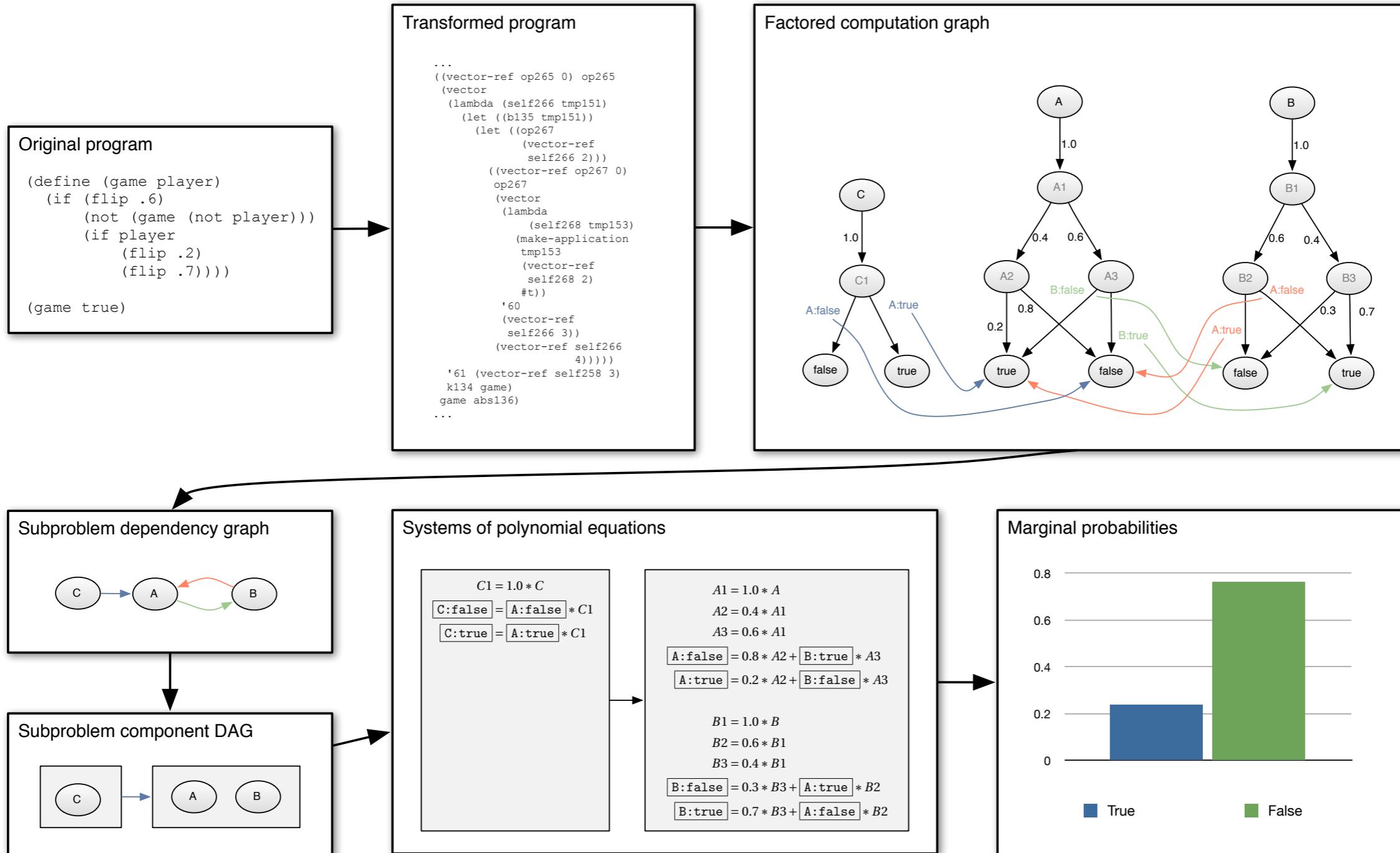
0.4

0.2

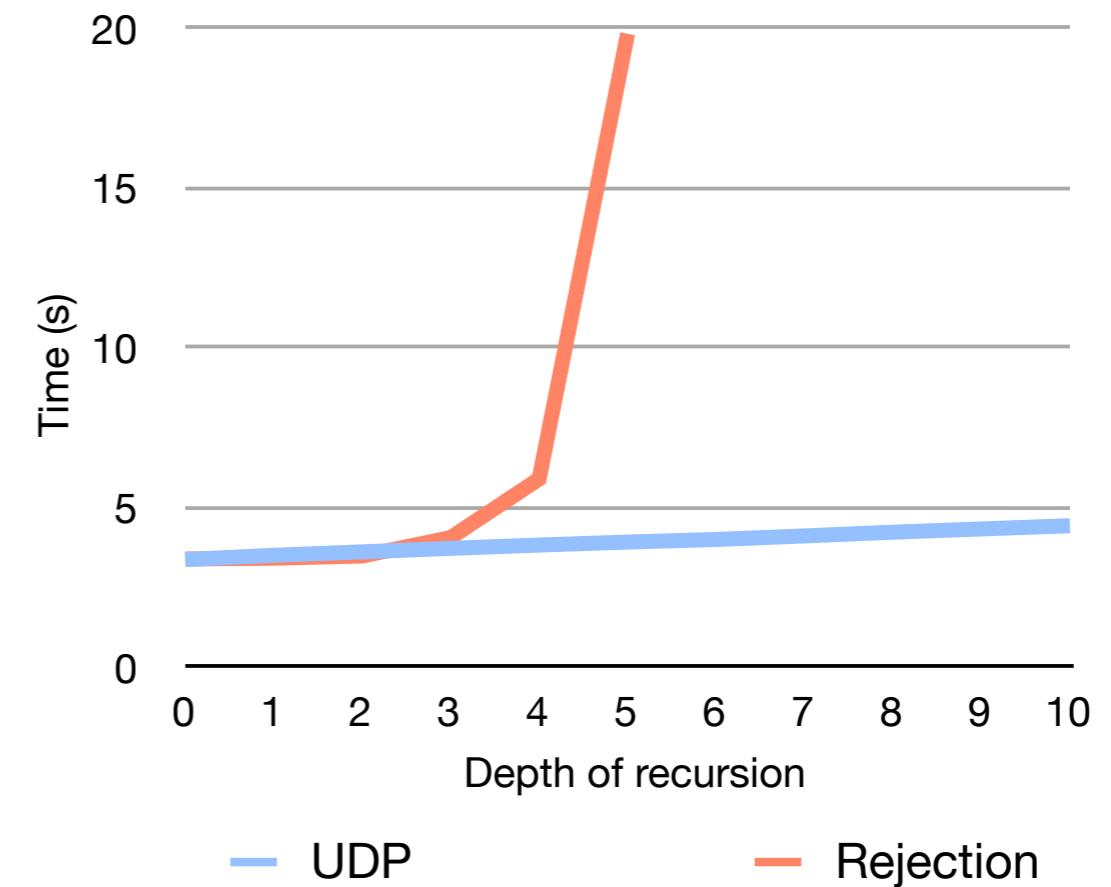
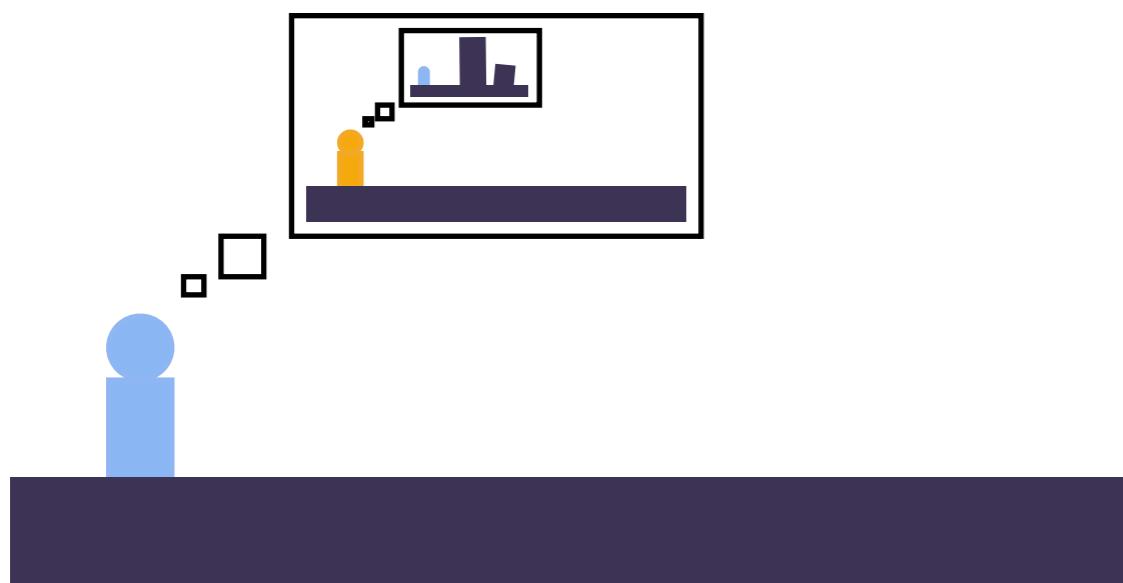
0

T

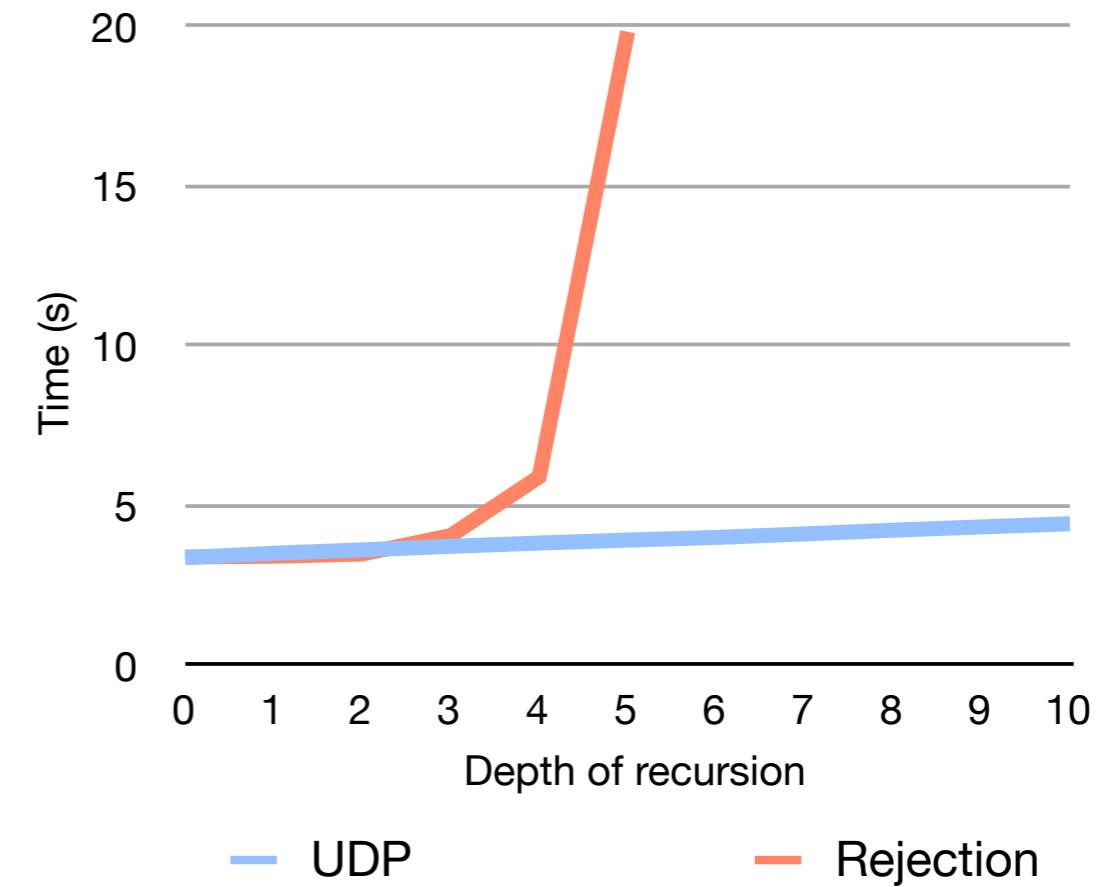
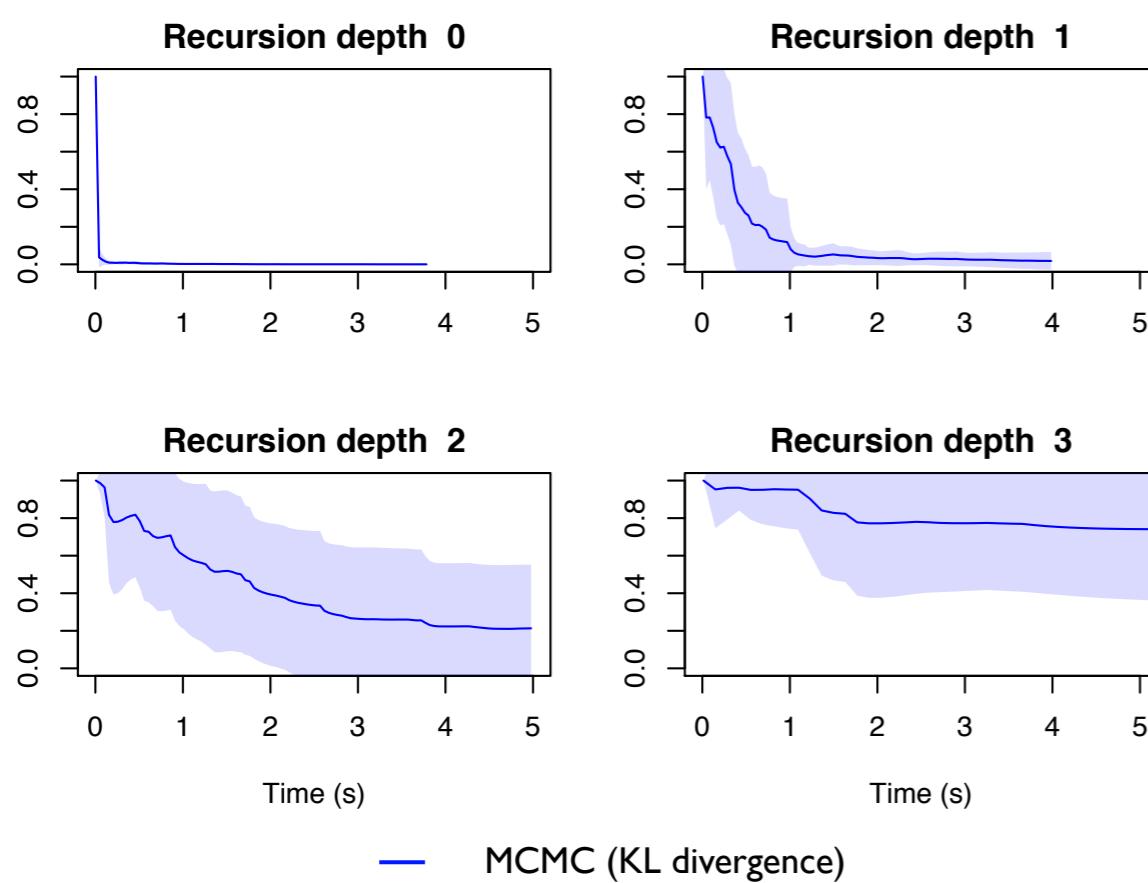




A simple coordination game



A simple coordination game



Cosh is a Church implementation based on the UDP algorithm:
github.com/stuhlmuller/cosh