

ICAPS 2014 Tutorial

Introduction to Planning Domain Modeling in RDDL

Scott Sanner



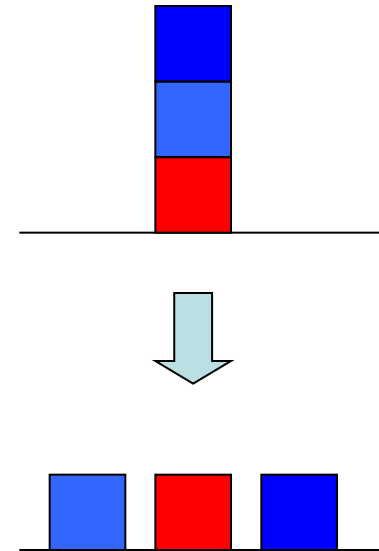
Observation

- Planning languages direct 5+ years of research
 - PDDL and variants
 - PPDDL
- Why?
 - Domain design is time-consuming
 - So everyone uses the existing benchmarks
 - Need for comparison
 - Planner code not always released
 - Only means of comparison is on competition benchmarks
- Implication:
 - We should choose our languages & problems well...

Current Stochastic Domain Language

- PPDDL
 - more expressive than PSTRIPS
 - for example, *probabilistic universal* and *conditional* effects:

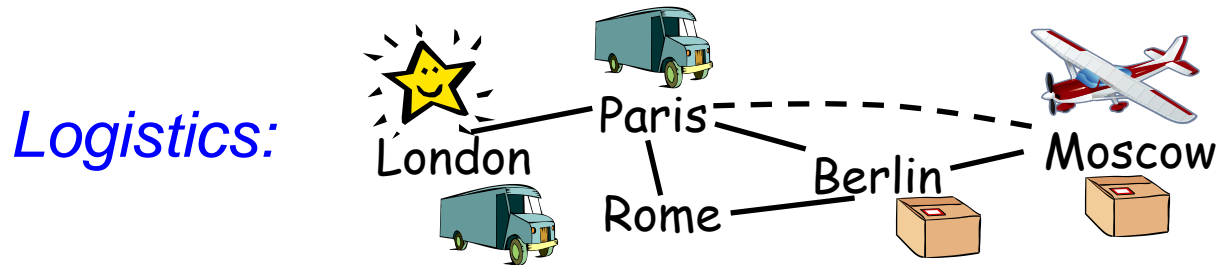
```
(:action put-all-blue-blocks-on-table
:parameters ( )
:precondition ( )
:effect (probabilistic 0.9
        (forall (?b)
          (when (Blue ?b)
            (not (OnTable ?b))))))
```











- But wait, not just BlocksWorld...
 - Colored BlocksWorld
 - Exploding BlocksWorld
 - Moving-stacks BlocksWorld
- Difficult problems *but where to apply solutions???*

More Realistic: Logistics

- Compact relational PPDDL Description:

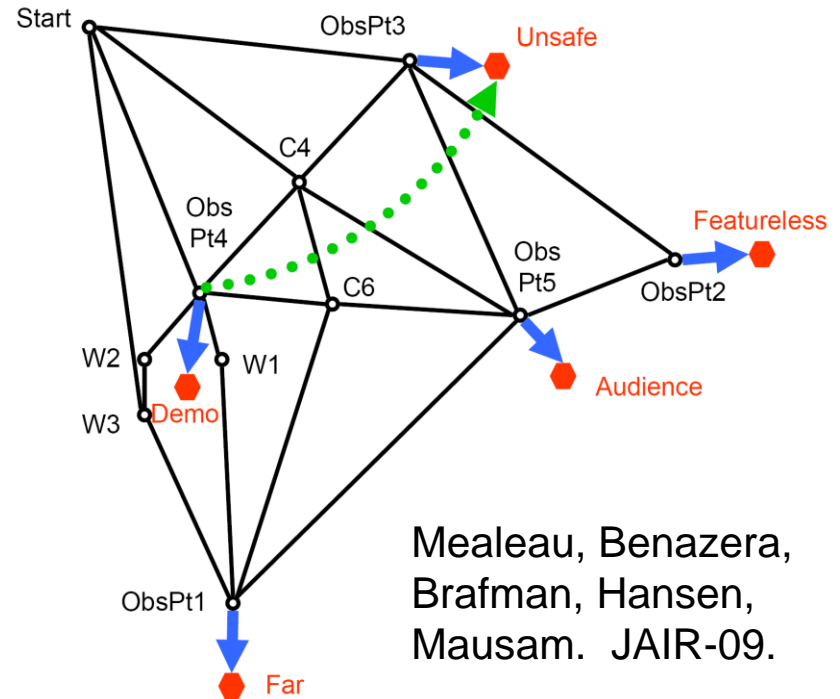


(:action load-box-on-truck-in-city
:parameters (*?b* - box *?t* - truck *?c* - city)
:precondition (and (BIn *?b* *?c*) (TIn *?t* *?c*))
:effect (and (On *?b* *?t*) (not (BIn *?b* *?c*))))

- Can instantiate problems for any domain objects
 - 3 trucks:    2 planes:   3 boxes:   
- But wait... only one truck can move at a time???
- No concurrency, no time: **will FedEx care?**

What stochastic problems
should we care about?

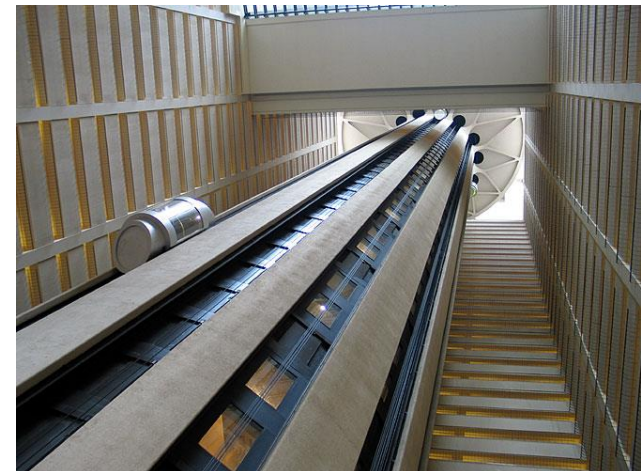
Mars Rovers



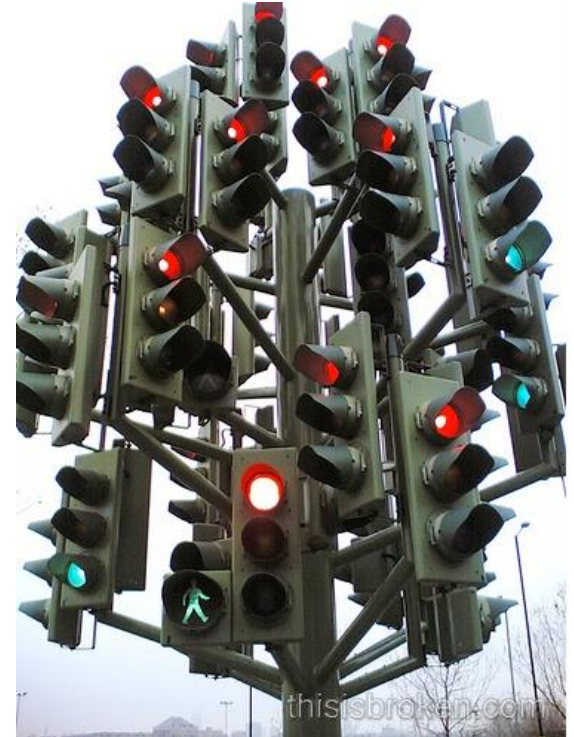
- Continuous
 - Time, robot position / pose, sun angle, ...
- Partially observable
 - Even worse: high-dimensional partially observable

Elevator Control

- **Concurrent Actions**
 - Elevator: up/down/stay
 - 6 elevators: 3^6 actions
- **Exogenous / Non-boolean:**
 - Random integer arrivals (e.g., Poisson)
- **Complex Objective:**
 - Minimize sum of wait times
 - Could even be nonlinear function (squared wait times)
- **Policy Constraints:**
 - People might get annoyed if elevator reverses direction



Traffic Control

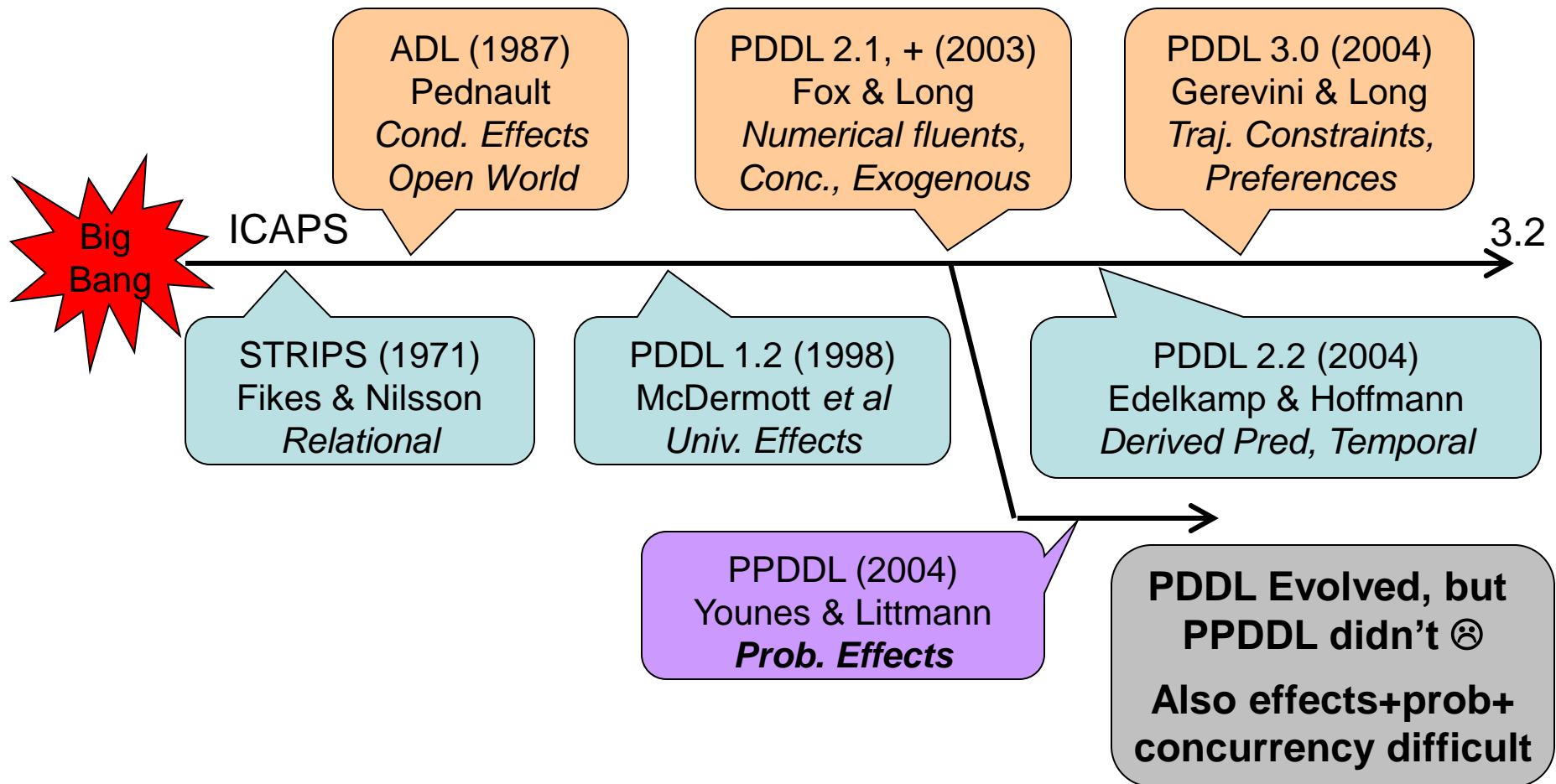


- Concurrent
 - Multiple lights
- Continuous Variables
 - Nonlinear dynamics
- Indep. Exogenous Events
 - Multiple vehicles
- Partially observable
 - Only observe stoplines

Can PPDDL model
these problems?

No? What happened?

A Brief History of (ICAPS) Time

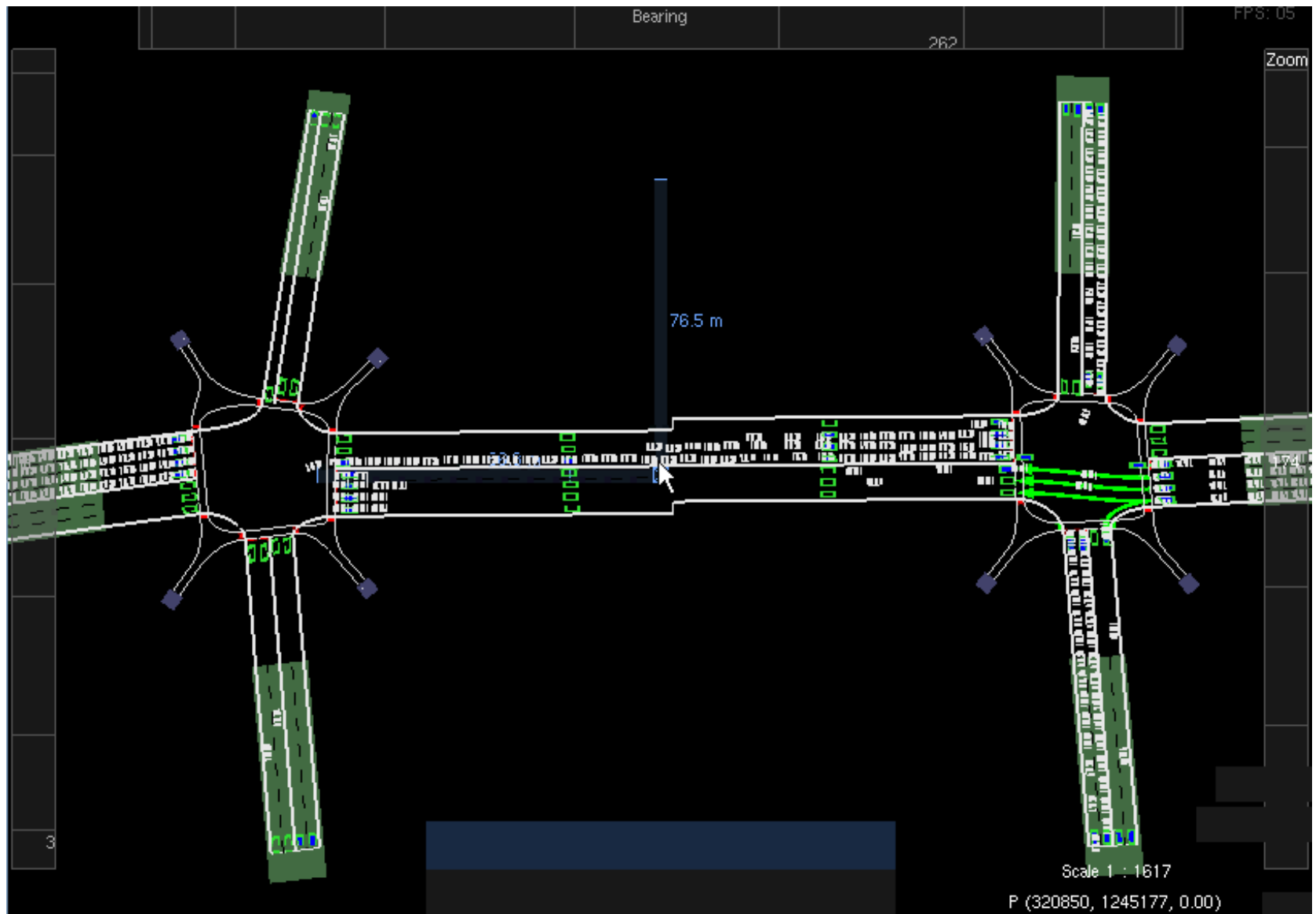


PDDL history from: <http://ipc.informatik.uni-freiburg.de/PddlResources>

What would it take to model
more realistic problems?

Let's take a deeper look at
traffic control...

Birth of RDDDL: Solving Traffic Control



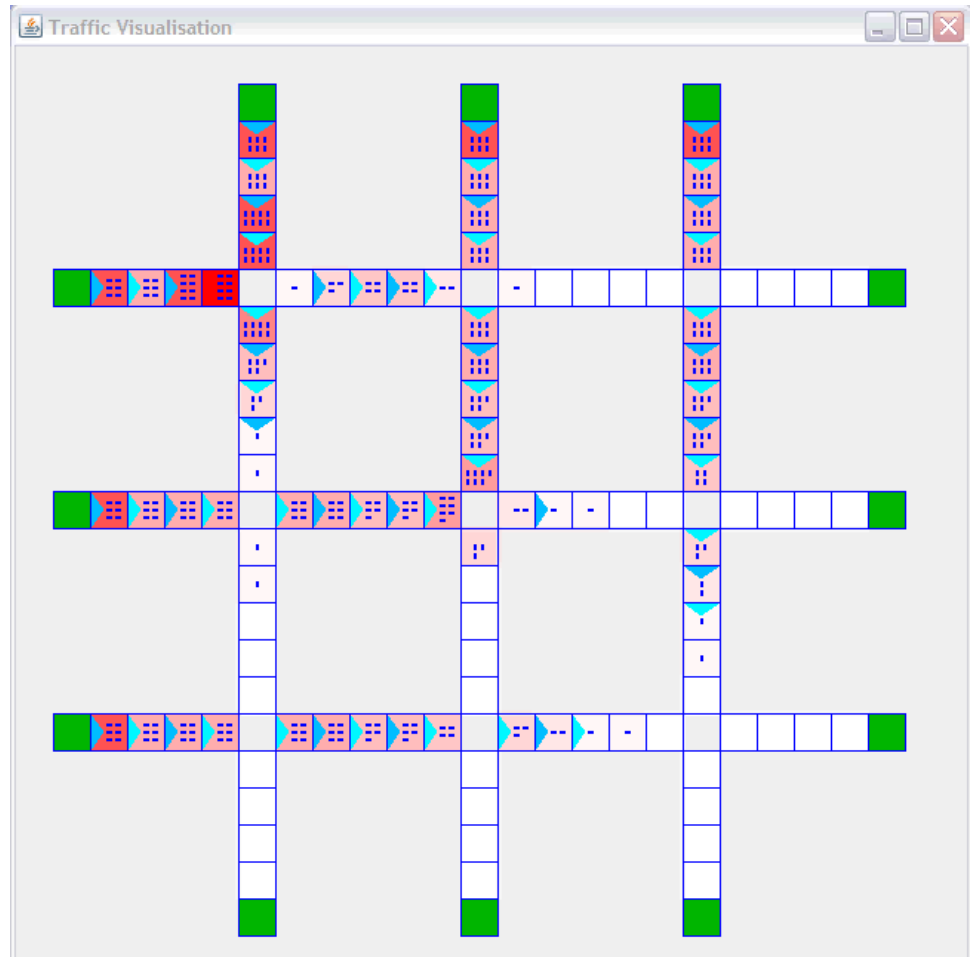
What's missing in PPDDL, Part I

- **Need Unrestricted Concurrency:**
 - In PPDDL, would have to enumerate joint actions
 - In PDDL 2.1: *restricted concurrency*
 - conflicting actions not executable
 - when effects probabilistic, some chance most effects conflict
 - really need *unrestricted concurrency* in probabilistic setting
- **Multiple Independent Exogenous Events:**
 - PPDDL only allows 1 independent event to affect fluent
 - E.g, what if cars in a queue change lanes, brake randomly?

Looking ahead... will need something more like Relational DBN

What's missing in PPDDL, Part II

- Expressive transition distributions:
 - (Nonlinear) stochastic difference equations
 - E.g., cell velocity as a function of traffic density
- Partial observability:
 - In practice, only observe stopline



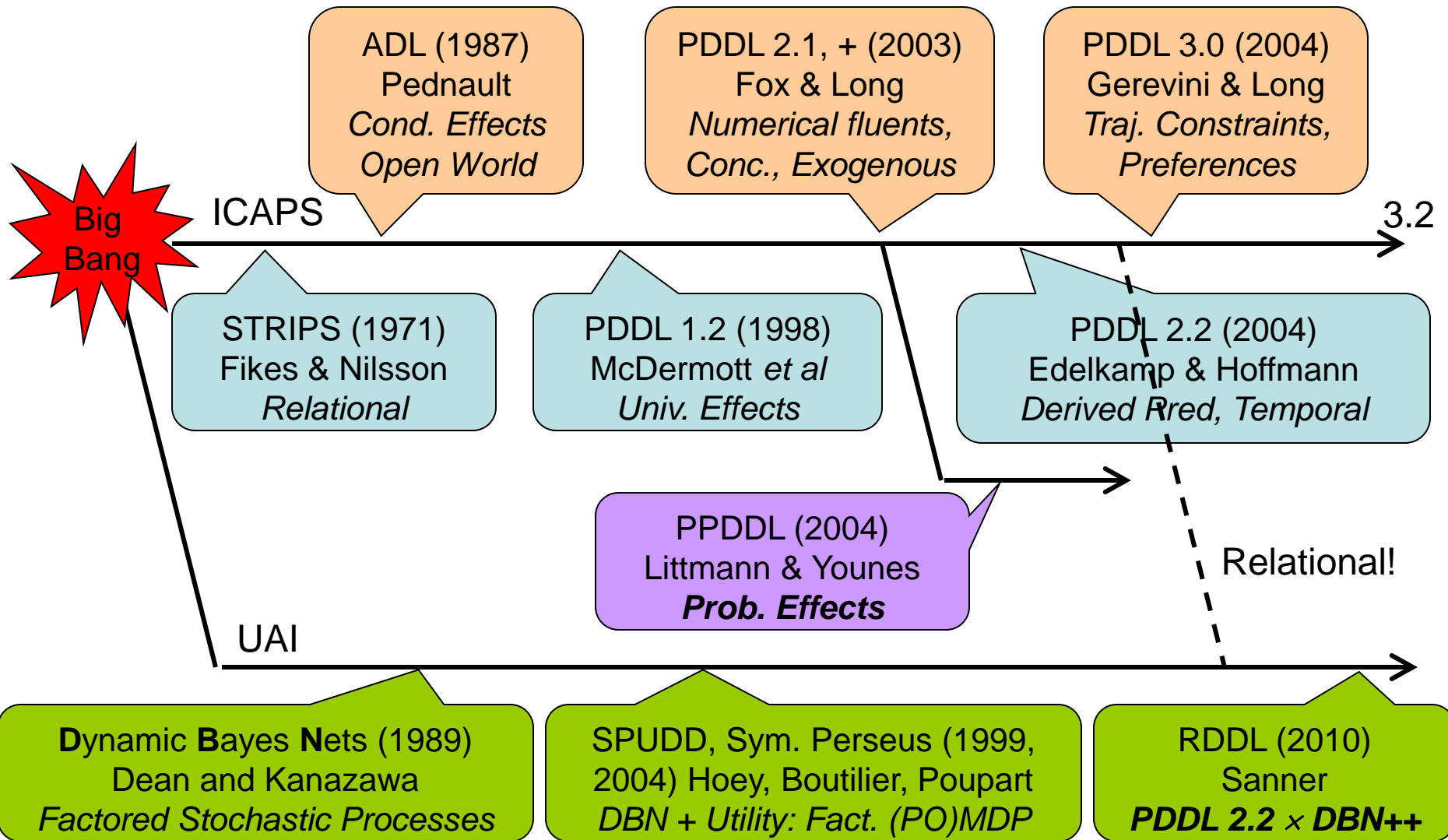
What's missing in PPDDL, Part III

- Distinguish fluents from nonfluents:
 - E.g., topology of traffic network
 - Lifted planners must know this to be efficient!
- Expressive rewards & probabilities:
 - E.g., sums, products, nonlinear functions, ratios, conditionals
- Global state-action constraints:
 - Concurrent domains need *global action* preconditions
 - E.g., two traffic lights cannot go into a given state
 - In logistics, vehicles cannot be in two different locations
 - Regression planners need state constraints!

Is there any hope?

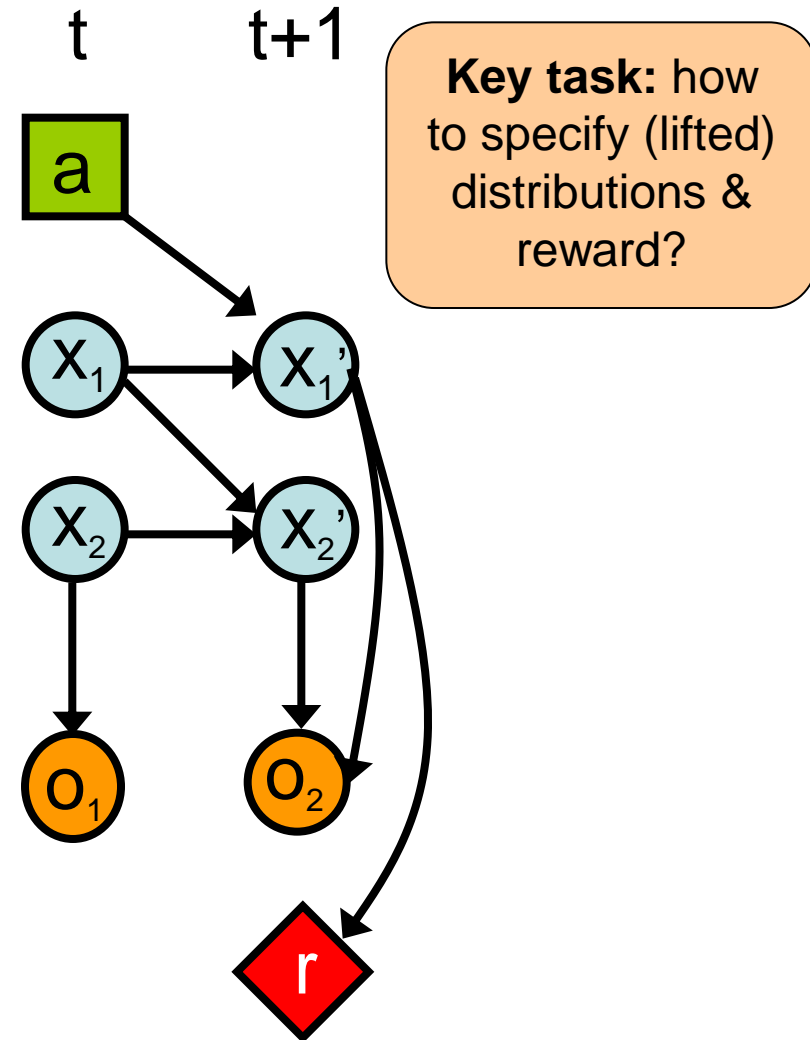
Yes, but we need to borrow from
factored MDP / POMDP community...

A Brief History of (ICAPS) Time



What is RDDDL?

- Relational Dynamic Influence Diagram Language
 - Relational
[DBN + Influence Diagram]
- Think of it as Relational SPUDD / Symbolic Perseus
 - on speed



RDDL Principles I

- Everything is a fluent (parameterized variable)
 - State fluents
 - Observation fluents
 - for partially observed domains
 - Action fluents
 - supports factored concurrency
 - Intermediate fluents
 - derived predicates, correlated effects, ...
 - Constant nonfluents (general constants, topology relations, ...)
- Flexible fluent types
 - Binary (predicate) fluents
 - Multi-valued (enumerated) fluents
 - Integer and continuous fluents (from PDDL 2.1)

RDDL Principles II

- **Semantics is ground DBN / Influence Diagram**
 - Unambiguous specification of transition semantics
 - Supports unrestricted concurrency
 - Naturally supports independent exogenous events

- **General expressions in transition / reward**

- Logical expressions ($\wedge, \vee, \Rightarrow, \Leftrightarrow, \forall, \exists$)
- Arithmetic expressions ($+, -, *, /, \Sigma_x, \Pi_x$)
- In/dis/equality comparison expressions ($=, \neq, <, >, \leq, \geq$)
- Conditional expressions (if-then-else, switch)
- Basic probability distributions
 - Bernoulli, Discrete, Normal, Poisson

Logical expr. $\{0,1\}$
so can use in
arithmetic expr.

Σ_x, Π_x aggregators over
domain objects extremely
powerful

RDDL Principles III

- Goal + General (PO)MDP objectives
 - Arbitrary reward
 - goals, numerical preferences (c.f., PDDL 3.0)
 - Finite horizon
 - Discounted or undiscounted
- State/action constraints
 - Encode legal actions
 - (concurrent) action preconditions
 - Assert state invariants
 - e.g., a package cannot be in two locations

RDDL Grammar

Let's examine BNF
grammar in infinite tedium!

OK, maybe not.
(Grammar [online](#) if you want it.)

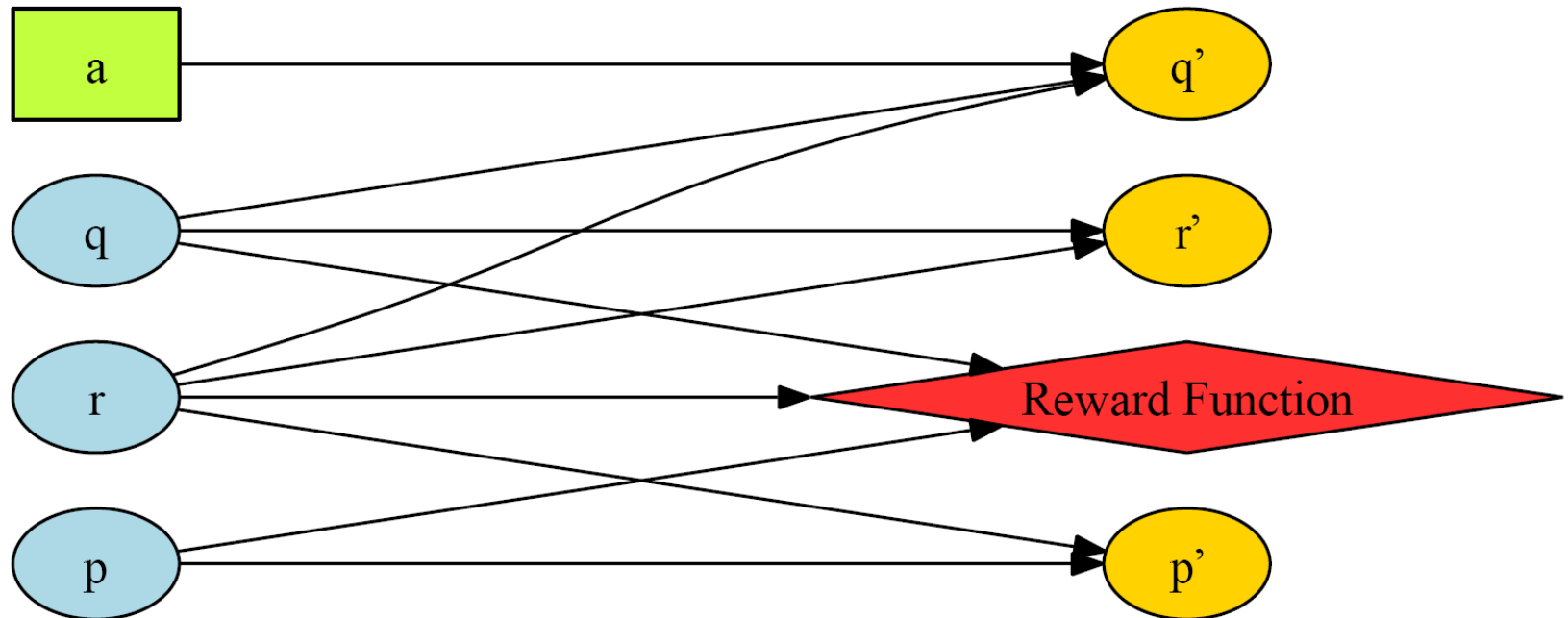
RDDL Examples

Easiest to understand
RDDL in use...

How to Represent Factored MDP?

Current State and Actions

Next State and Reward



p	r	p'	$P(p' p,r)$
true	true	true	0.9
true	true	false	0.1
true	false	true	0.3
true	false	false	0.7
false	true	true	0.3
false	true	false	0.7
false	false	true	0.3
false	false	false	0.7

RDDL Equivalent

```
// Define the state and action variables (not parameterized here)
pvariables {
    p : { state-fluent, bool, default = false };
    q : { state-fluent, bool, default = false };
    r : { state-fluent, bool, default = false };
    a : { action-fluent, bool, default = false };
};

// Define the conditional probability function for each
// state variable in terms of previous state and action
cpfs {
    p' = if (p ^ r) then Bernoulli(.9) else Bernoulli(.3);

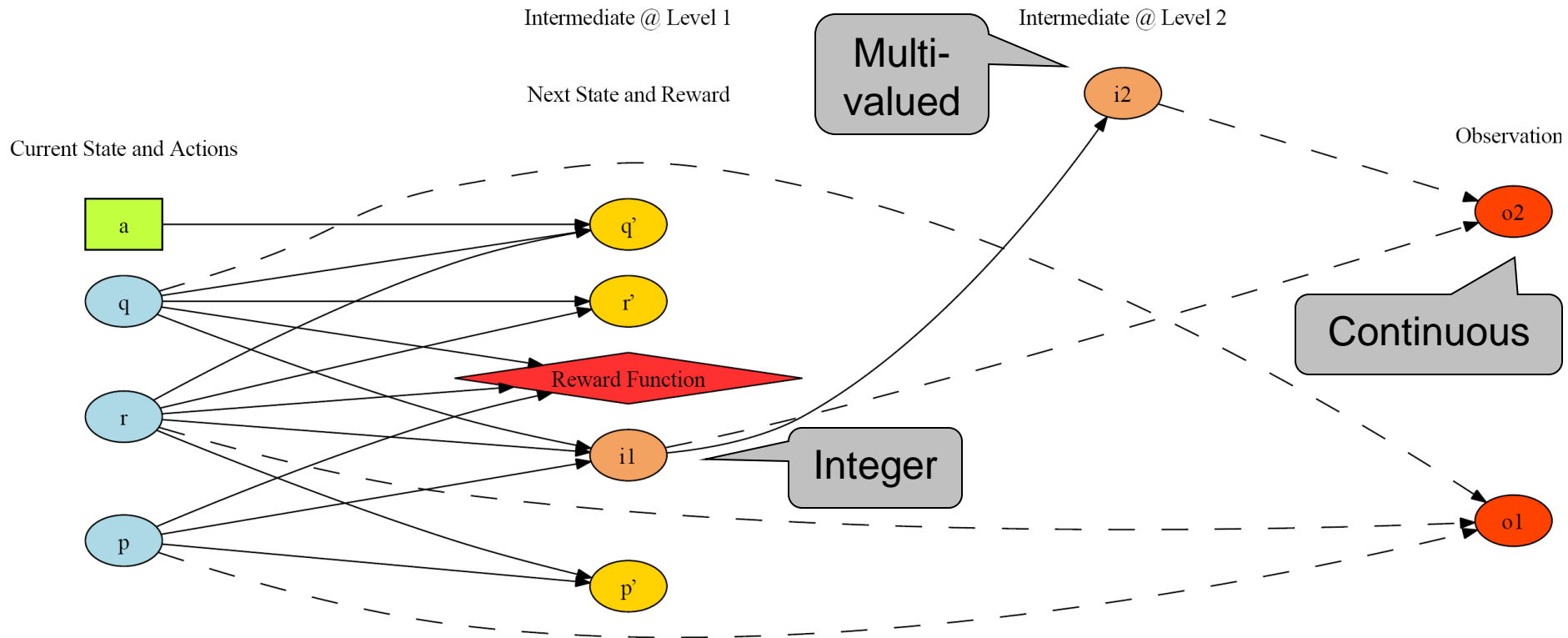
    q' = if (q ^ r) then Bernoulli(.9)
        else if (a) then Bernoulli(.3) else Bernoulli(.8);

    r' = if (~q) then KronDelta(r) else KronDelta(r <=> q);
};

// Define the reward function; note that boolean functions are
// treated as 0/1 integers in arithmetic expressions
reward = p + q - r;
```

Can think of
transition
distributions
as “*sampling
instructions*”

A Discrete-Continuous POMDP?



A Discrete-Continuous POMDP, Part I

```
// User-defined types
types {
    enum_level : {@low, @medium, @high}; // An enumerated type
};

pvariables {
    p : { state-fluent, bool, default = false };
    q : { state-fluent, bool, default = false };
    r : { state-fluent, bool, default = false };

    i1 : { interm-fluent, int, level = 1 };
    i2 : { interm-fluent, enum_level, level = 2 };

    o1 : { observ-fluent, bool };
    o2 : { observ-fluent, real };

    a : { action-fluent, bool, default = false };
};

cpfs {

    // Some standard Bernoulli conditional probability tables
    p' = if (p ^ r) then Bernoulli(.9) else Bernoulli(.3);

    q' = if (q ^ r) then Bernoulli(.9)
        else if (a) then Bernoulli(.3) else Bernoulli(.8);

    // KronDelta is a delta function for a discrete argument
    r' = if (~q) then KronDelta(r) else KronDelta(r <=> q);
}
```

A Discrete-Continuous POMDP, Part II

Integer

```
// Just set i1 to a count of true state variables  
i1 = KronDelta(p + q + r);
```

Multi-
valued

```
// Choose a level with given probabilities that sum to 1  
i2 = Discrete(enum_level,  
              @low : if (i1 >= 2) then 0.5 else 0.2,  
              @medium : if (i1 >= 2) then 0.2 else 0.5,  
              @high : 0.3  
              );
```

Real

```
// Note: Bernoulli parameter must be in [0,1]  
o1 = Bernoulli( (p + q + r)/3.0 );
```

Mixture of
Normals

```
// Conditional linear stochastic equation  
o2 = switch (i2) {  
    case @low      : i1 + 1.0 + Normal(0.0, i1*i1),  
    case @medium   : i1 + 2.0 + Normal(0.0, i1*i1/2.0),  
    case @high     : i1 + 3.0 + Normal(0.0, i1*i1/4.0) };  
};
```

Variance comes from other
previously sampled variables

RDDL so far...

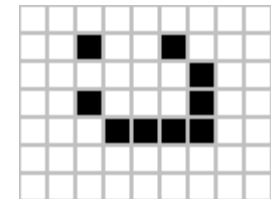
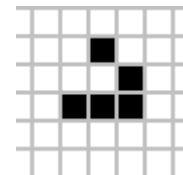
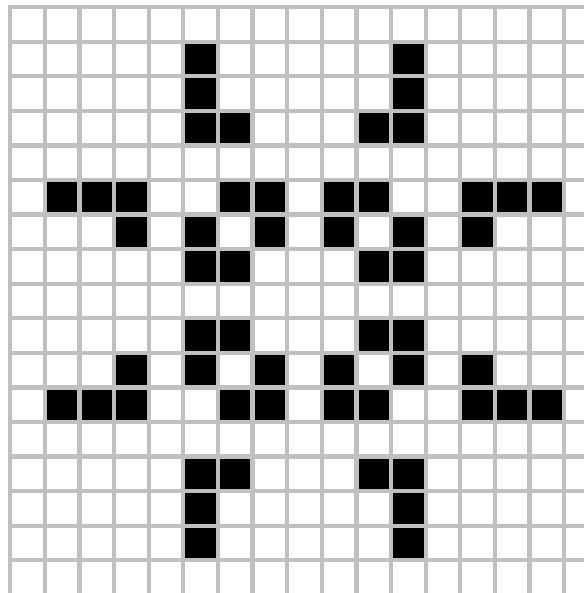
- Mainly SPUDD / Symbolic Perseus with a different syntax 😊
 - A few enhancements
 - concurrency
 - constraints
 - integer / continuous variables
- **Real problems (e.g., traffic) need lifting**
 - An intersection model
 - A vehicle model
 - Specify each intersection / vehicle model once!

Lifting: Conway's Game of Life

(simpler than traffic)

- Cells born, live, die based on neighbors

- < 2 or > 3 neighbors:
cell dies
- 2 or 3 neighbors:
cell lives
- 3 neighbors
→ cell birth!
- Make into MDP
 - Probabilities
 - Actions to turn on cells
 - Maximize number of cells on



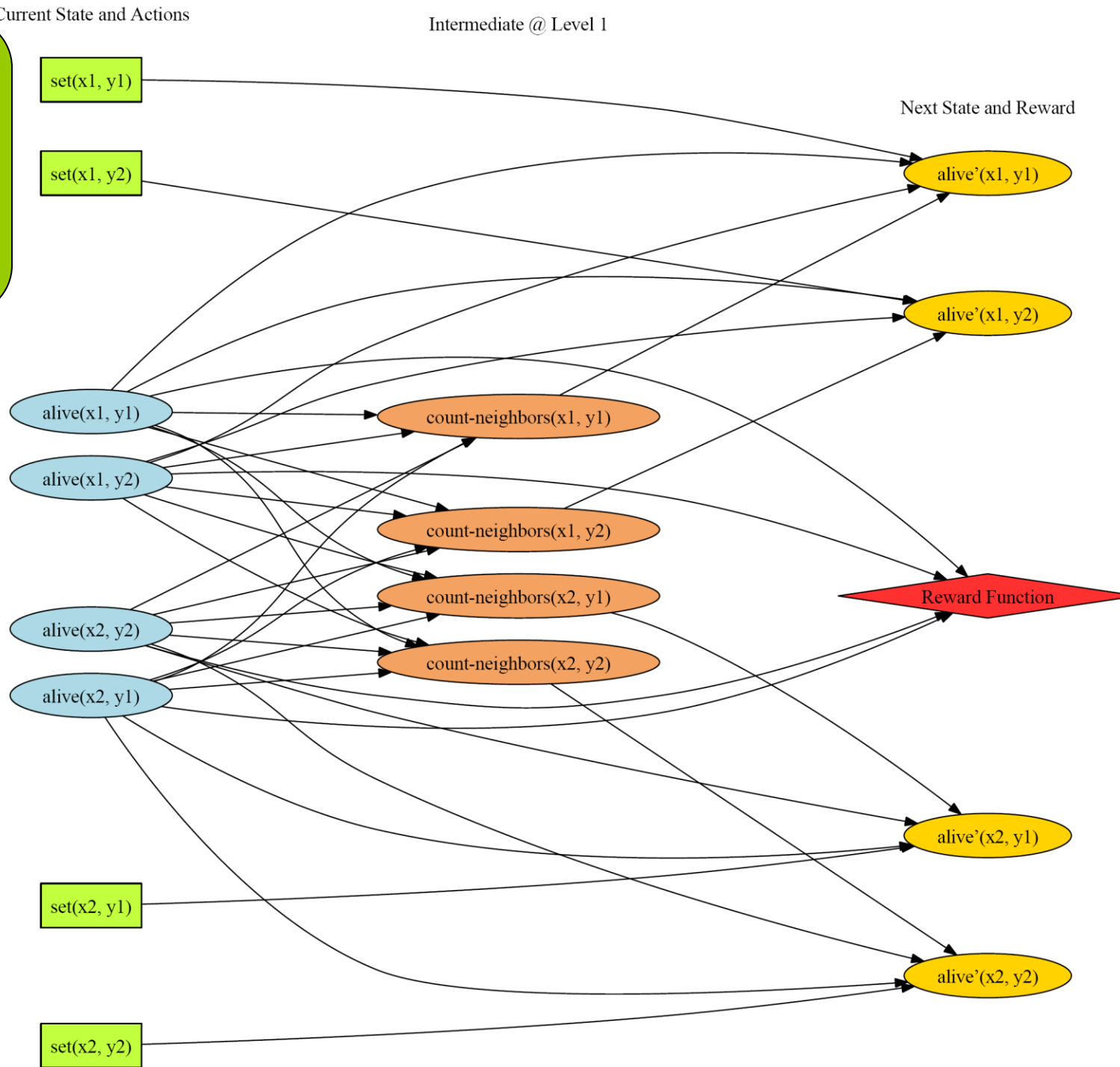
http://en.wikipedia.org/wiki/Conway's_Game_of_Life

- Compact RDDDL specification for **any** grid size? Lifting.

Concurrency
as factored
action variables

How many
possible joint
actions here?

Lifted MDP: Game of Life



A Lifted MDP

```
// Store alive-neighbor count
count-neighbors(?x,?y) =
```

Intermediate variable: like derived predicate

```
  KronDelta(sum_{?x2 : x_pos, ?y2 : y_pos}
    [NEIGHBOR(?x,?y,?x2,?y2) ^ alive(?x2,?y2)]);
```

```
// Determine whether cell (?x,?y) is alive in next state
alive'(?x,?y) = if (forall_{?y2 : y_pos} ~alive(?x,?y2))
  then Bernoulli(PROB_REGENERATE) // Rule 6
    ^ (count-neighbors(?x,?y) >= 2)
    ^ (count-neighbors(?x,?y) <= 3)]
  | [~alive(?x,?y)
    ^ (count-neighbors(?x,?y) == 3)]
  | set(?x,?y))
  then Bernoulli(PROB_REGENERATE)
  else Bernoulli(1.0 - PROB_REGENERATE);
```

Using counts to
decide next state

```
};
```

```
// Reward is number of alive cells
reward = sum_{?x : x_pos, ?y : y_pos} alive(?x,?y);
```

Additive reward!

```
state-action-constraints {
  // Assertion: ensure PROB_REGENERATE is a valid probability
  (PROB_REGENERATE >= 0.0) ^ (PROB_REGENERATE <= 1.0);
```

State constraints,
preconditions

```
// Precondition: perhaps we should not set a cell if already alive
forall_{?x : x_pos, ?y : y_pos} alive(?x,?y) => ~set(?x,?y);
};
```

Nonfluent and Instance Definition

```
// Define numerical and topological constants
```

```
non-fluents game2x2 {  
    domain = game_of_life;  
    objects {  
        x_pos : {x1,x2};  
        y_pos : {y1,y2};  
    };  
};
```

Objects that don't
change b/w instances

Numerical constant
nonfluent

Topologies over
these objects

```
non-fluents {  
    PROB_REGENERATE = 0.9; // Numerical constants are just non-fluents  
    NEIGHBOR(x1,y1,x1,y2); NEIGHBOR(x1,y1,x2,y1); NEIGHBOR(x1,y1,x2,y2);  
    NEIGHBOR(x1,y2,x1,y1); NEIGHBOR(x1,y2,x2,y1); NEIGHBOR(x1,y2,x2,y2);  
    NEIGHBOR(x2,y1,x1,y1); NEIGHBOR(x2,y1,x1,y2); NEIGHBOR(x2,y1,x2,y2);  
    NEIGHBOR(x2,y2,x1,y1); NEIGHBOR(x2,y2,x1,y2); NEIGHBOR(x2,y2,x2,y1);  
};  
}
```

```
instance is1 {  
    domain = game_of_life;  
    non-fluents = game2x2;  
    init-state {  
        alive(x1,y1);  
        alive(x2,y2);  
    };  
};
```

Import a topology

Initial state as usual

```
max-nondef-actions = 3; // Allow up to 3 cells to be set concurrently  
horizon = 20;  
discount = 0.9;
```

Concurrency

```
}
```

Power of Lifting

Simple domains
can generate
complex DBNs!

non-fluents game2x2 {

domain = game_of_life;

objects {

x_pos : {x1,x2};
y_pos : {y1,y2};

};

non-fluents {

PROB_REGENERATE = 0.9;

NEIGHBOR(x1,y1,x1,y2);
NEIGHBOR(x1,y1,x2,y1);
NEIGHBOR(x1,y1,x2,y2);

NEIGHBOR(x1,y2,x1,y1);
NEIGHBOR(x1,y2,x2,y1);
NEIGHBOR(x1,y2,x2,y2);

NEIGHBOR(x2,y1,x1,y1);
NEIGHBOR(x2,y1,x1,y2);
NEIGHBOR(x2,y1,x2,y2);

NEIGHBOR(x2,y2,x1,y1);
NEIGHBOR(x2,y2,x1,y2);
NEIGHBOR(x2,y2,x2,y1);

};

non-fluents game3x3 {

domain = game_of_life;

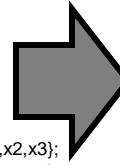
objects {

x_pos : {x1,x2,x3};
y_pos : {y1,y2,y3};

};

non-fluents {

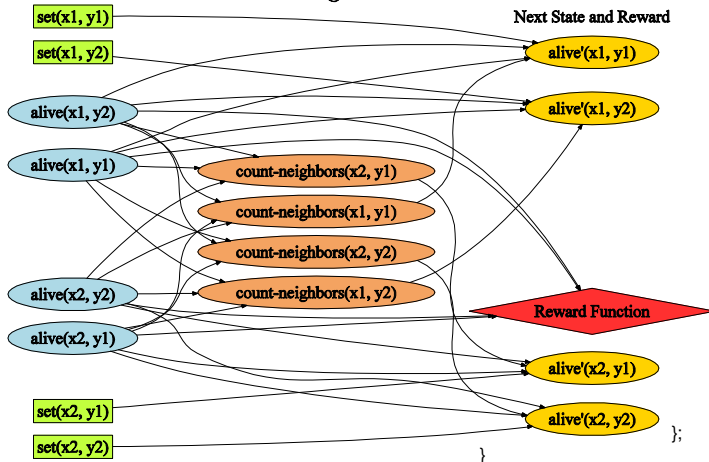
NEIGHBOR(x1,y1,x1,y2);
NEIGHBOR(x1,y1,x2,y1);
NEIGHBOR(x1,y1,x2,y2);
NEIGHBOR(x1,y2,x1,y1);
NEIGHBOR(x1,y2,x2,y1);
NEIGHBOR(x1,y2,x2,y2);
NEIGHBOR(x1,y2,x2,y3);
NEIGHBOR(x1,y2,x1,y3);
NEIGHBOR(x1,y3,x1,y2);
NEIGHBOR(x1,y3,x2,y2);
NEIGHBOR(x1,y3,x2,y3);
NEIGHBOR(x2,y1,x1,y1);
NEIGHBOR(x2,y1,x1,y2);
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NEIGHBOR(x2,y2,x3,y2);
NEIGHBOR(x2,y2,x3,y3);
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NEIGHBOR(x2,y3,x2,y2);
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NEIGHBOR(x2,y3,x3,y2);
NEIGHBOR(x2,y3,x3,y3);
NEIGHBOR(x3,y1,x2,y2);
NEIGHBOR(x3,y1,x3,y2);
NEIGHBOR(x3,y2,x2,y2);
NEIGHBOR(x3,y2,x2,y3);
NEIGHBOR(x3,y2,x3,y3);
NEIGHBOR(x3,y3,x2,y3);
NEIGHBOR(x3,y3,x2,y2);
NEIGHBOR(x3,y3,x3,y2);



Current State and Actions

Intermediate @ Level 1

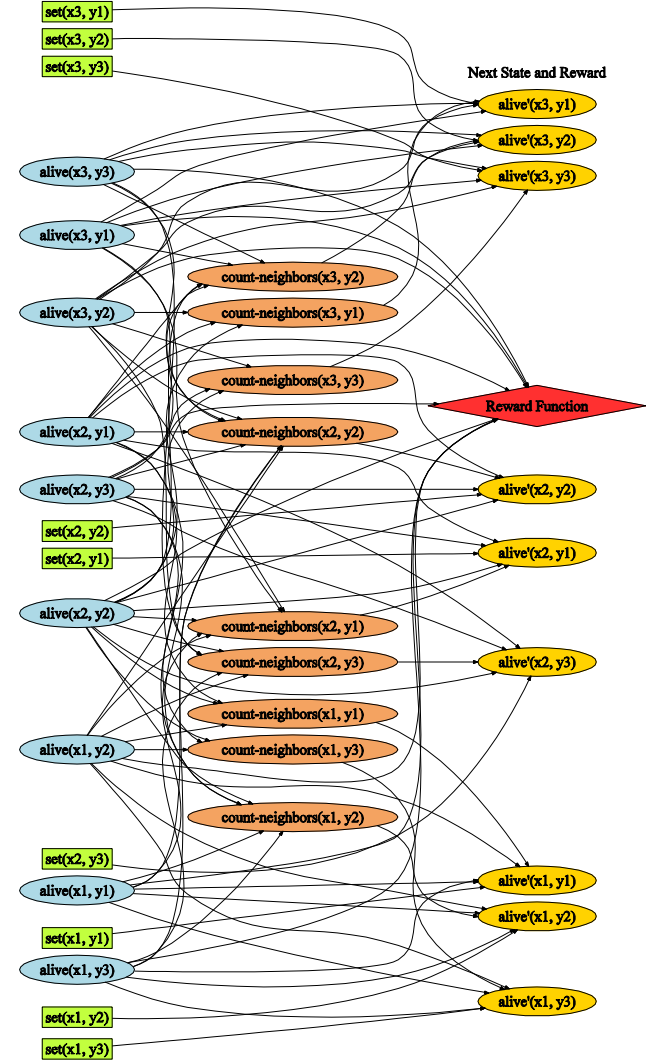
Next State and Reward



Current State and Actions

Intermediate @ Level 1

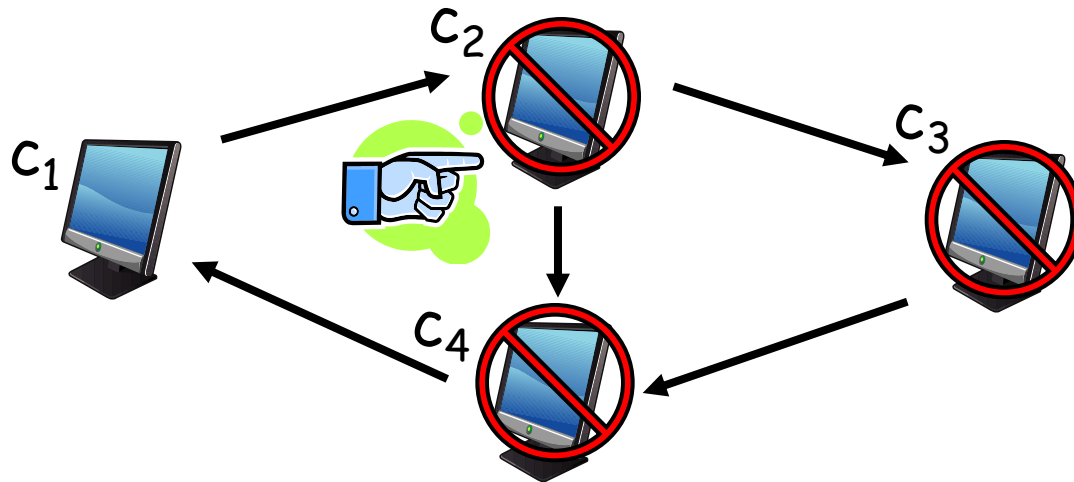
Next State and Reward



Complex Lifted Transitions: SysAdmin

SysAdmin (Guestrin et al, 2001)

- Have n computers $C = \{c_1, \dots, c_n\}$ in a network
- **State:** each computer c_i is either “up” or “down”



- **Transition:** computer is “up” proportional to its state and # upstream connections that are “up”
- **Action:** manually reboot one computer
- **Reward:** +1 for every “up” computer

Complex Lifted Transitions

SysAdmin (Guestrin et al, 2001)

```
pvariables {
```

```
  REBOOT-PROB : { non-fluent, real, default = 0.1 };
```

```
  REBOOT-PENALTY : { non-fluent, real, default = 0.75 };
```

```
  CONNECTED(computer, computer) : { non-fluent, bool, default = false };
```

```
  running(computer) : { state-fluent, bool, default = false };
```

```
  reboot(computer) : { action-fluent, bool, default = false };
```

```
};
```

```
cpfs {
```

```
  running'(?x) = if (reboot(?x))
```

```
    then KronDelta(true) // if
```

```
    else if (running(?x)) // else
```

```
      then Bernoulli(
```

```
        .5 + .5*[1 + sum_{?y : computer} (CONNECTED(?y,?x) ^ running(?y))]
        / [1 + sum_{?y : computer} CONNECTED(?y,?x)]
```

```
      else Bernoulli(REBOOT-PROB);
```

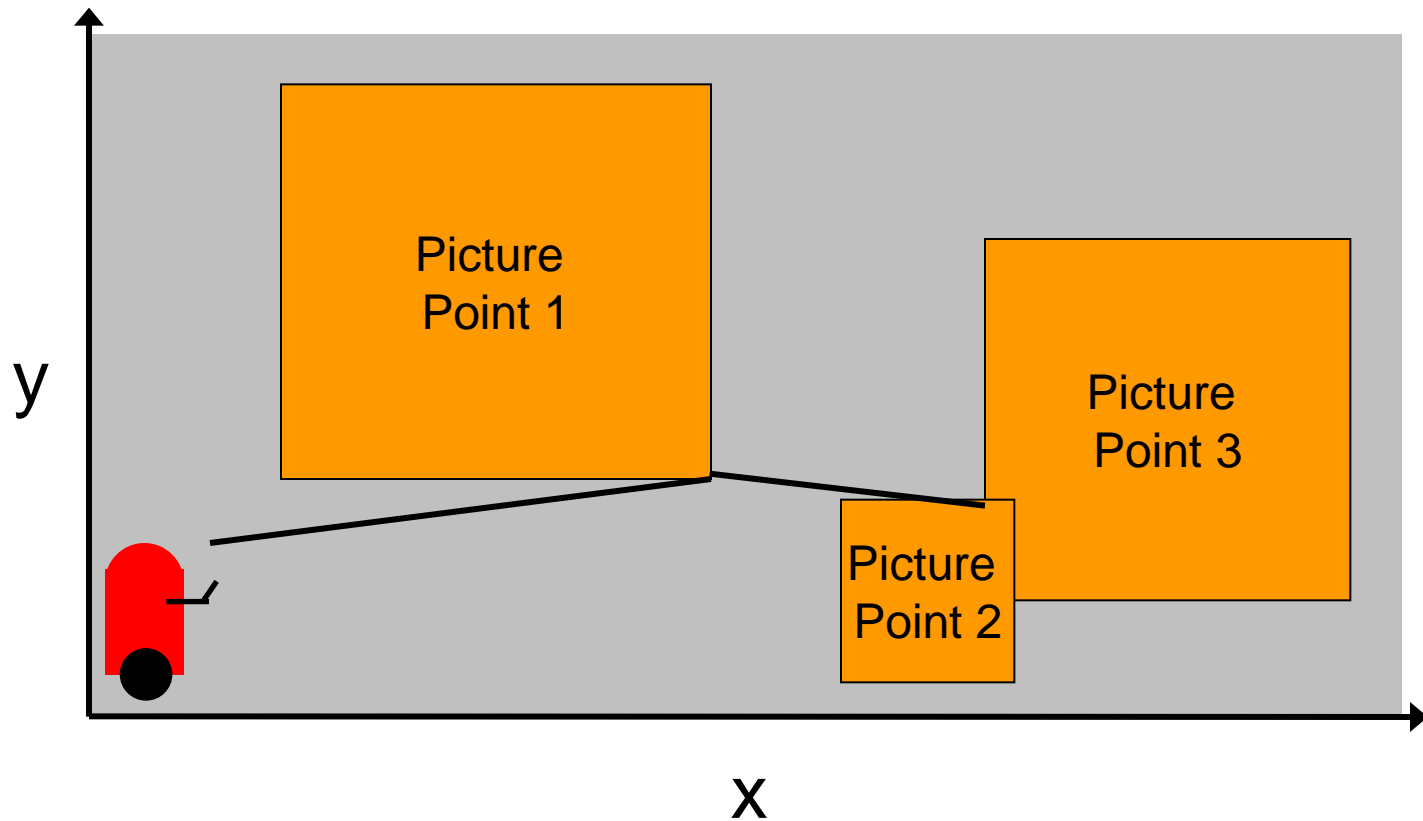
```
};
```

```
reward = sum_{?c : computer} [running(?c) - (REBOOT-PENALTY * reboot(?c))];
```

Probability of a
computer running
depends on ratio of
connected
computers running!

then must be running
network properties

Lifted Continuous MDP in RDDL: Simple Mars Rover



Simple Mars Rover: Part I

```
types { picture-point : object; };
```

```
pvariables {
```

Constant
picture
points,
bounding box

```
    PICT_XPOS(picture-point) : { non-fluent, real, default = 0.0 };  
    PICT_YPOS(picture-point) : { non-fluent, real, default = 0.0 };  
    PICT_VALUE(picture-point) : { non-fluent, real, default = 1.0 };  
    PICT_ERROR_ALLOW(picture-point) : { non-fluent, real, default = 0.5 };
```

Rover position
(only one
rover)
and time

```
    xPos : { state-fluent, real, default = 0.0 };  
    yPos : { state-fluent, real, default = 0.0 };  
    time : { state-fluent, real, default = 0.0 };
```

Rover
actions

```
    xMove      : { action-fluent, real, default = 0.0 };  
    yMove      : { action-fluent, real, default = 0.0 };  
    snapPicture : { action-fluent, bool, default = false };
```

Question, how
to make multi-
rover?

Simple Mars Rover: Part II

```
cpfs {
```

```
// Noisy movement update
```

```
xPos' = xPos + xMove + Normal(0.0, MOVE_VARIANCE_MULT*xMove);
```

```
yPos' = yPos + yMove + Normal(0.0, MOVE_VARIANCE_MULT*yMove);
```

```
// Time update
```

```
time' = if (snapPicture)
```

```
then DiracDelta(time + 0.25)
```

```
else DiracDelta(time +
```

```
[if (xMove > 0) then xMove else -xMove] +
```

```
[if (yMove > 0) then yMove else -yMove]);
```

Fixed time for picture

White noise, variance
proportional to distance moved

Time proportional to
distance moved

```
};
```

nb., This is RDDDL1, in
RDDDL2, now have vectors
and functions like abs()

Simple Mars Rover: Part III

// We get a reward for any picture taken within picture box error bounds
// and the time limit.

```
reward = if (snapPicture ^ (time <= MAX_TIME))  
    then sum_{?p : picture-point} [  
        if ((xPos >= PICT_XPOS(?p) - PICT_ERROR_ALLOW(?p))  
            ^ (xPos <= PICT_XPOS(?p) + PICT_ERROR_ALLOW(?p))  
  
            ^ (yPos >= PICT_YPOS(?p) - PICT_ERROR_ALLOW(?p))  
            ^ (yPos <= PICT_YPOS(?p) + PICT_ERROR_ALLOW(?p)))  
        then PICT_VALUE(?p)  
        else 0.0 ]  
    else 0.0;
```

Reward for all pictures taken
within bounding box!

state-action-constraints {

// Cannot snap a picture and move at the same time.
snapPicture => ((xMove == 0.0) ^ (yMove == 0.0));

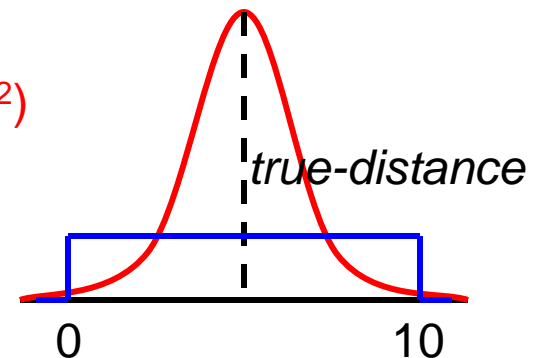
};

Cannot move and take
picture at same time.

How to Think About Distributions

- **Transition distribution is stochastic program**
 - Similar to BLOG (Milch, Russell, et al), IBAL (Pfeffer)
 - Leaves of programs are distributions
 - Think of SPUDD / Sym. Perseus decision diagrams as having Bernoulli leaves
- *Procedural specification of sampling process*
 - Use intermediate DBN variables for storage
 - E.g., drawing a distance measurement in robotics
 - **boolean** *Noise* := sample from **Bernoulli** (.1)
 - **real** *Measurement* := If (*Noise* == true)
 - Then sample from **Uniform**(0, 10)
 - Else sample from **Normal**(true-distance, σ^2)

Convenient way to write complex mixture models and conditional distributions that occur in practice!



RDDL Recap I

- Everything is a fluent (parameterized variable)
 - State fluents
 - Observation fluents
 - for partially observed domains
 - Action fluents
 - supports factored concurrency
 - Intermediate fluents
 - derived predicates, correlated effects, ...
 - Constant nonfluents (general constants, topology relations, ...)
- Flexible fluent types
 - Binary (predicate) fluents
 - Multi-valued (enumerated) fluents
 - Integer and continuous fluents (from PDDL 2.1)

RDDL Recap II

- **Semantics is ground DBN / Influence Diagram**
 - Unambiguous specification of transition semantics
 - Supports unrestricted concurrency
 - Naturally supports independent exogenous events

- **General expressions in transition / reward**

- Logical expressions ($\wedge, \vee, \Rightarrow, \Leftrightarrow, \forall, \exists$)
- Arithmetic expressions ($+, -, *, /, \Sigma_x, \Pi_x$)
- In/dis/equality comparison expressions ($=, \neq, <, >, \leq, \geq$)
- Conditional expressions (if-then-else, switch)
- Basic probability distributions
 - Bernoulli, Discrete, Normal, Poisson

Logical expr. $\{0,1\}$
so can use in
arithmetic expr.

Σ_x, Π_x aggregators over
domain objects extremely
powerful

RDDL Recap III

- Goal + General (PO)MDP objectives
 - Arbitrary reward
 - goals, numerical preferences (c.f., PDDL 3.0)
 - Finite horizon
 - Discounted or undiscounted
- State/action constraints
 - Encode legal actions
 - (concurrent) action preconditions
 - Assert state invariants
 - e.g., a package cannot be in two locations

RDDL Software

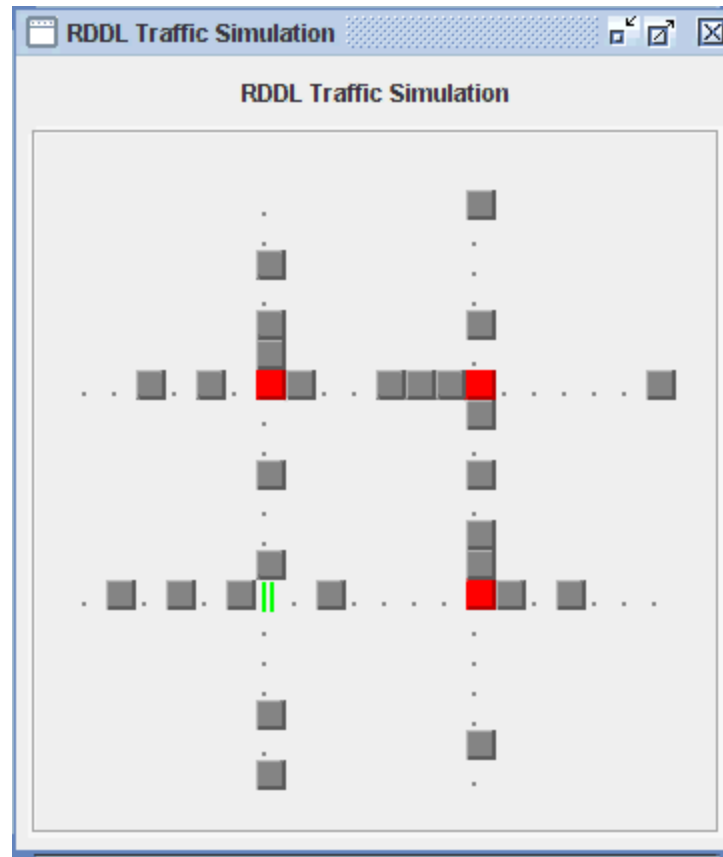
Open source & online at

<http://code.google.com/p/rddlsim/>

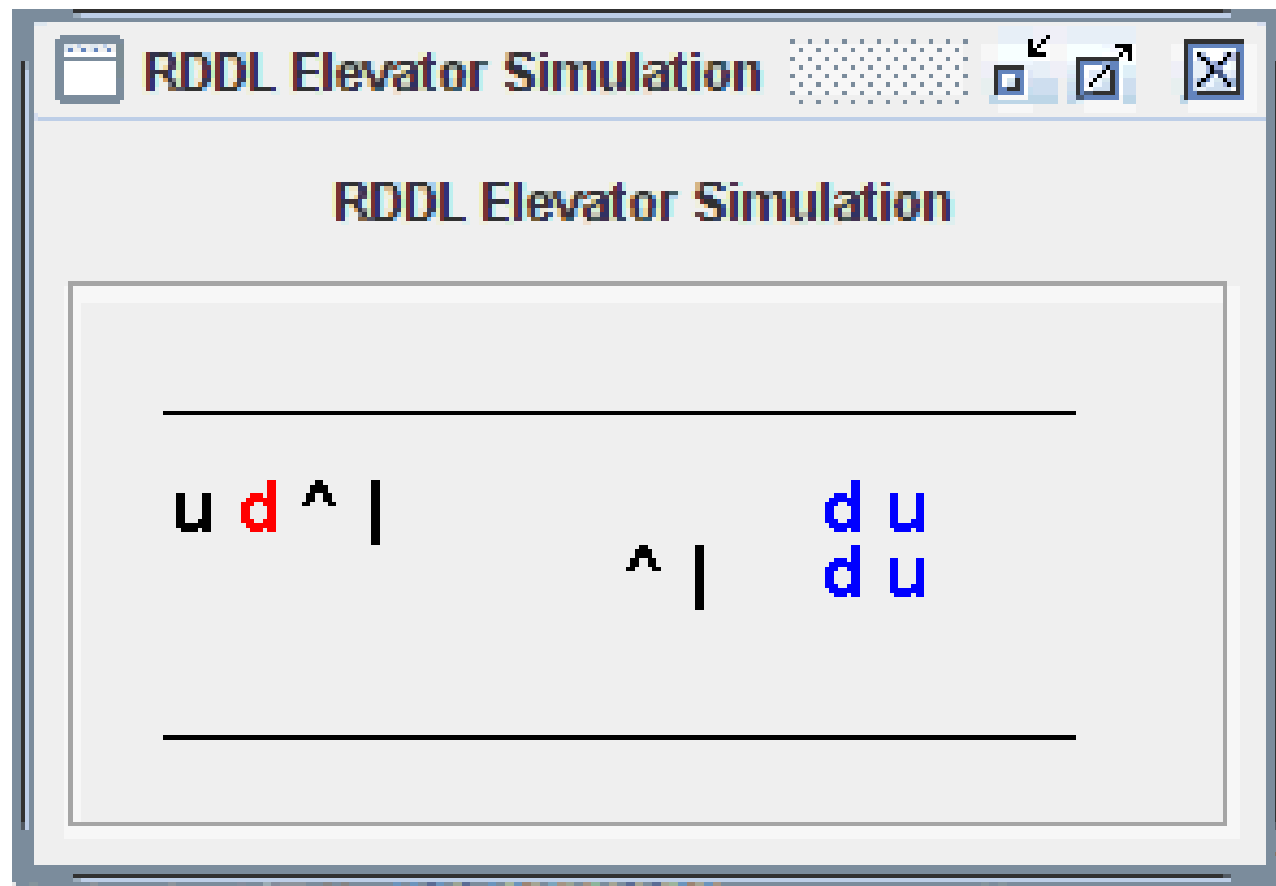
Java Software Overview

- BNF grammar and parser
- Simulator
- Automatic translations
 - LISP-like format (easier to parse)
 - SPUDD & Symbolic Perseus (boolean subset)
 - Ground PPDDL (boolean subset)
- Client / Server
 - Evaluation scripts for log files
- Visualization
 - DBN Visualization
 - Domain Visualization – see how your planner is doing

Visualization of Boolean Traffic



Visualization of Boolean Elevators



Submit your own
Domains in RDDDL!

Field only makes true progress
working on realistic problems

RDDL2 (with Thomas Keller)

- Elementary functions
 - abs, sin, cos, log, exp, pow, sqrt, etc.
- Vectors
 - Need for some distributions (multinomial, multivariate normal)
- Object fluents and bounded integers
 - \$ to differentiate object names from parameter-free fluents
 - @ to differentiate bounded-range integers from integers
 - Auto-casting where possible
- Derived fluents
 - Like intermediate but can use in preconditions
- Indefinite horizon (goal-oriented problems)
- Recursion!
 - Fluents can self-reference as long as define a DAG

RDDL Domain Examples

- See IPPC 2011 (Discrete)
 - http://users.cecs.anu.edu.au/~ssanner/IPPC_2011/index.html
- See IPPC 2014 (Discrete)
 - https://cs.uwaterloo.ca/~mgrzes/IPPC_2014/
- See IPPC 2014/5 (Continuous)
 - http://users.cecs.anu.edu.au/~ssanner/IPPC_2014/index.html

Ideas for other RDDDL Domains

- UAVs with partial observability
- (Hybrid) Control
 - Linear-quadratic control (Kalman filtering with control)
 - Discrete and continuous actions – avoided by planning
 - Nonlinear control
- Dynamical Systems from other fields
 - Population dynamics
 - Chemical / biological systems
 - Physical systems
 - Pinball!
 - Environmental / climate systems
- Bayesian Modeling
 - Continuous Fluents can represent parameters
 - Beta / Bernoulli / Dirichlet / Multinomial / Gaussian
 - Then progression is a Bayesian update!
 - Bayesian reinforcement learning

RDDL3?

- Effects-based specification?
 - Easier to write than current fluent-centered approach
 - But how to resolve conflicting effects in unrestricted concurrency
- Timed processes?
 - Concurrency + time quite difficult
 - Should we simply use languages like RMPL (Williams *et al*)
 - Or could there be RDDL + RMPL hybrids?

Enjoy RDDDL!

(no lack of difficult
problems to solve!)

Questions?