ICAPS 2023 Tutorial

Introduction to Domain Modeling in RDDL Part 1: Language Overview

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Multiple Target Audiences

- ICAPS folks familiar with (P)PDDL wondering what RDDL is and when they might use it
- Planning language agnostics who are simply interested in planning for MDPs and POMDPs
- RL researchers interested in how to specify and exploit complex model structure

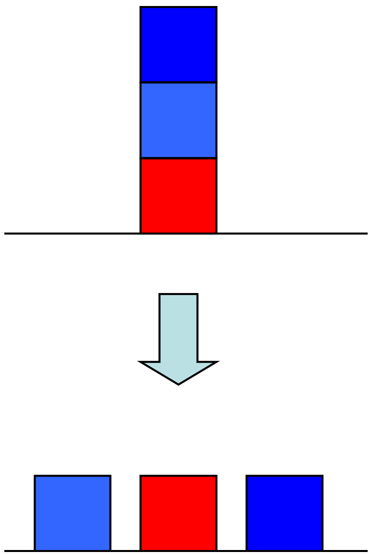
RDDL Tutorial Outline

- Part 1: Language Overview
  - **What is probabilistic planning in PPDDL?**
  - Why do we need RDDL?
  - RDDL by example
  - Overview of RDDL solution methodologies
- Part 2: PyRDDLGym

Stochastic Domain Languages as of 2009

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

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



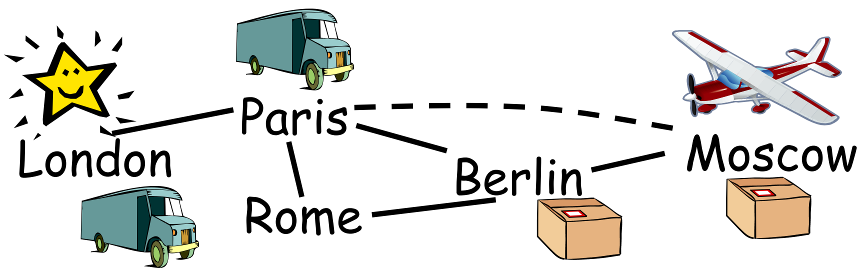
- **Idea:** make some effects stochastic

- **Question:** is this sufficient to model realistic problems?

More Realistic: Logistics?

- PPDDL Description:

Logistics:



(:action load-box-on-truck-in-city
:parameters (?b - box ?t - truck ?c – city)
:precondition (and (BIn ?b ?c) (TIn ?t ?c))
*:effect (**prob 0.7** (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?**

Expressivity Limitations of PPDDL

- Many PPDDL domains were tweaks of PDDL domains
  - Recipe: add success probability on some effects
    - e.g., *load-plane(p,x)* succeeds with prob 0.9
  - IPPC 2004/6, could win by determinizing / replanning
    - led to work on "probabilistically interesting" PPDDL problems (Little & Thiebaux, 2007)
- But what stochastic expressiveness is needed for modeling real-world domains?
  - Then we can ask what language is appropriate

Observation

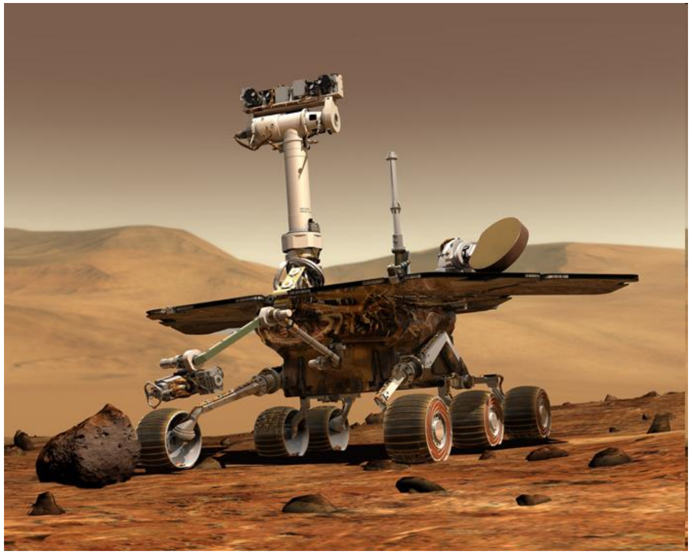
- Planning languages direct 5+ years of research
  - PDDL and variants
  - Probabilistic PDDL (PPDDL)

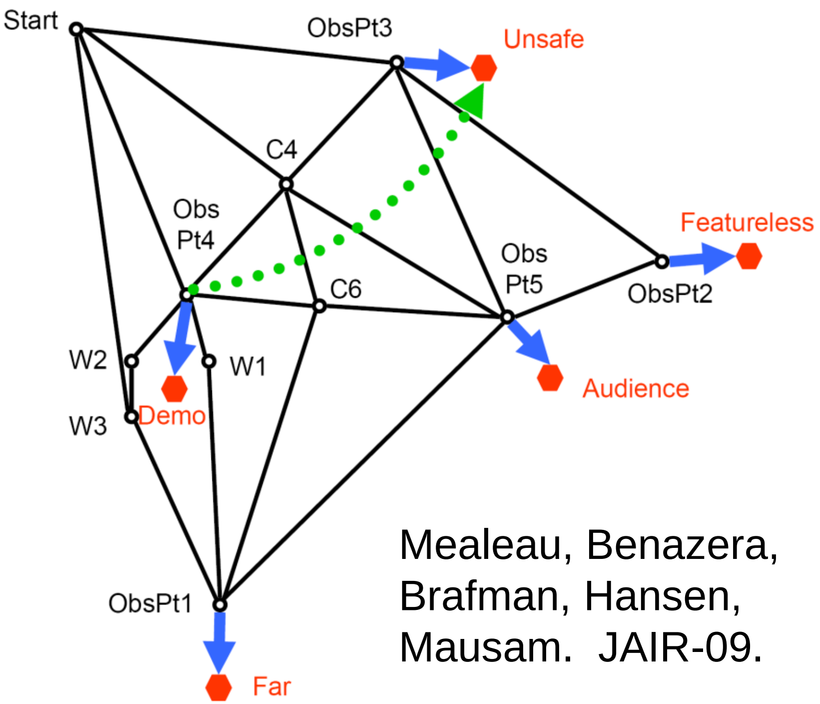
- Why?
  - Domain design is time-consuming
    - So everyone (students) use existing benchmarks
  - Need for comparison
    - Planner code not always released
    - Only means of comparison is on competition benchmarks

- Implication:
  - We should choose our languages & problems well
  - Let’s ask what problems we want to model / solve

What probabilistic problems might we want to model?

Mars Rovers





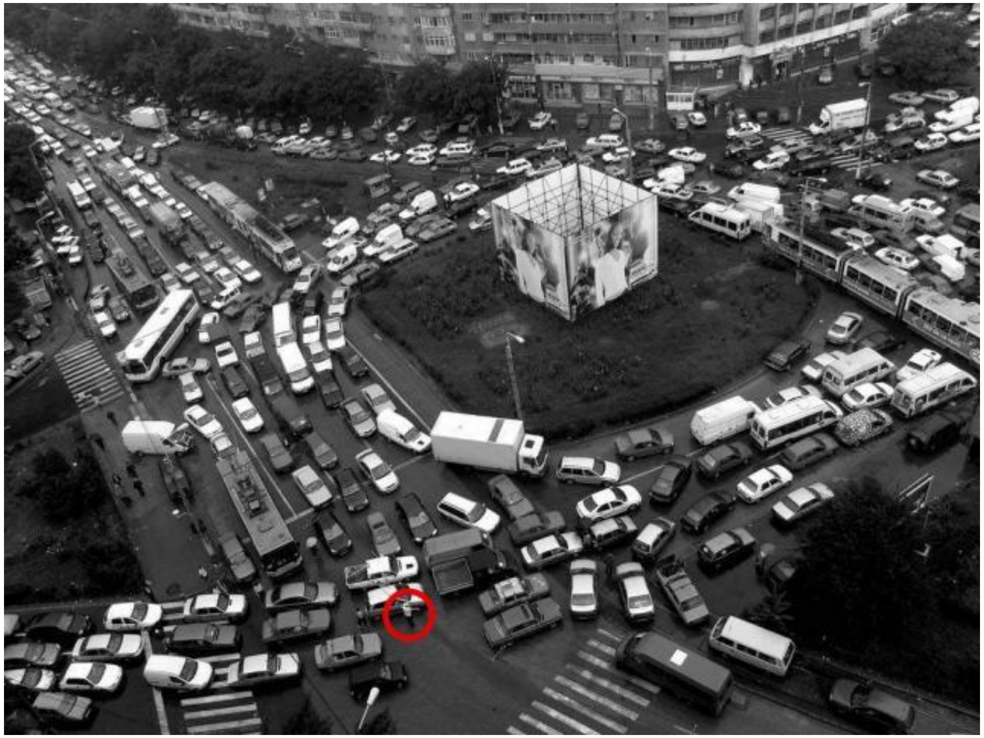
Mealeau, Benazera, Brafman, Hansen, Mausam. JAIR-09.

- Continuous
  - Time, robot position / pose, sun angle, battery reserves…
- 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) at every floor
- Complex Objective
  - Minimize sum of wait times
  - Could even be nonlinear function (squared wait times)
- Complex Action Constraints
  - People might get annoyed if elevator reverses direction

Traffic Control



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

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What are we missing in PPDDL?

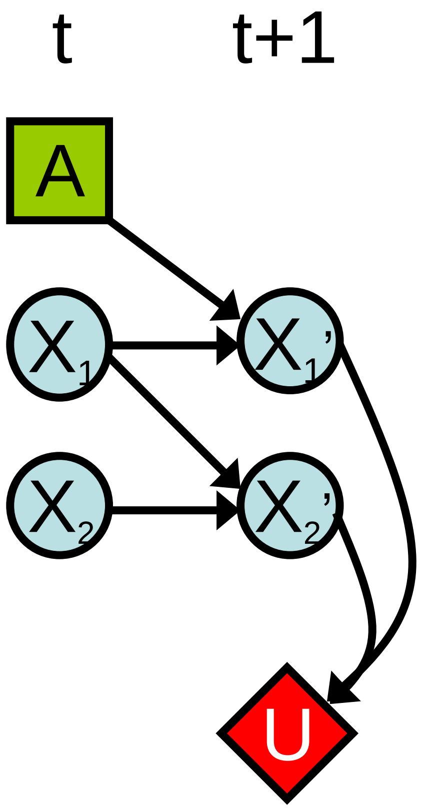
- Independent concurrent stochastic actions & events
  - Exogenous stochastic events that scale with domain size
    - Random person arrivals at elevator floors, traffic movement
    - Probabilities that are a complex function of state
  - Resolution of stochastic or concurrent event conflicts
    - Two elevators admit passengers from same floor
  - Preconditions over joint actions (not per action)
    - Joint traffic light configurations must adhere to safety constraints
- Remedy: action-centric (P)PDDL → fluent-centric RDDL

Need expressive decision-making formalism that supports complex stochastic **fluent** updates

Relational Dynamic Bayes Net
+ Influence Diagram (RDDL)

a.k.a. Relational Factored MDP

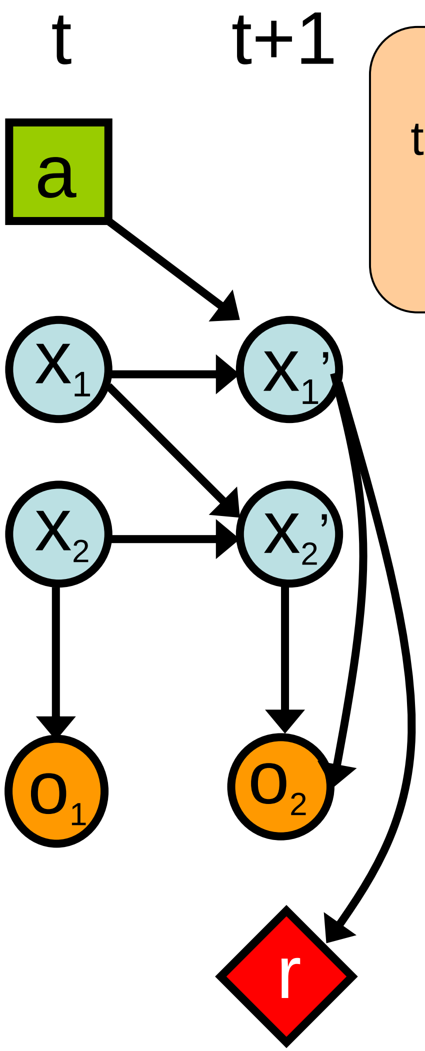
Dynamical Models & Influence Diagrams



- Dynamic Bayes Nets (DBNs) …
  - Represent state @ times t, t+1
    - Assume stationary distribution
- Influence Diagrams (IDs)…
  - Action nodes [squares]
    - Not random variables
    - Rather "controlled" variables
  - Utility nodes <diamonds>
    - A utility conditioned on state, e.g. $U(X_1', X_2')$ = if $(X_1' = X_2')$ then 10 else 0

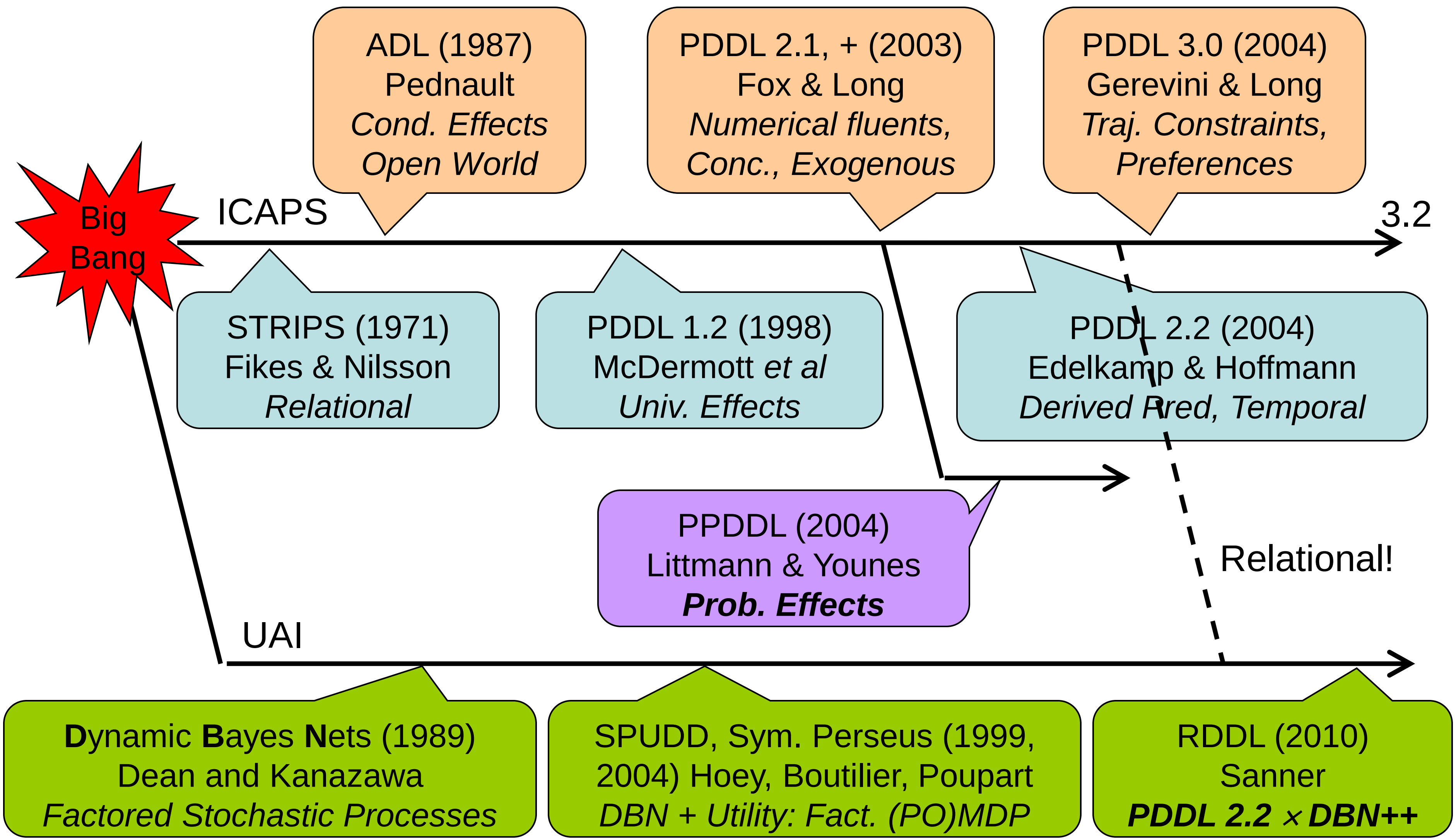
What is RDDL?

- Relational Dynamic Influence Diagram Language
  - Relational [DBN + Influence Diagram]
- Think of it as a Relational Factored (PO)MDP
  - Fluent updates are probabilistic programs



Key task: how to specify (lifted) distributions & reward?

A Brief History of (ICAPS) Time



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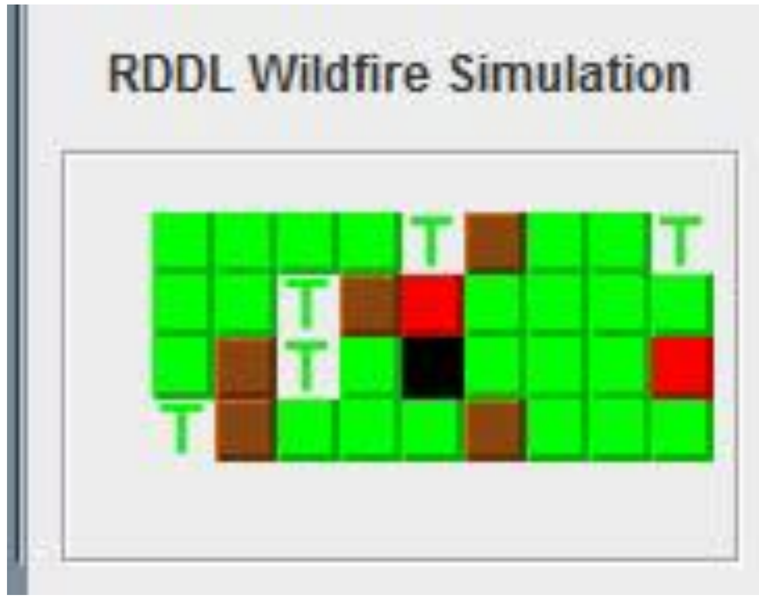
Example:

How to specify a problem in RDDL (that cannot be expressed in PPDDL)

Wildfire Domain



- Contributed by Zhenyu Yu (School of Economics and Management, Tongji University)
  - Karafyllidis, I., & Thanailakis, A. (1997). *A model for predicting forest fire spreading using gridular automata*. Ecological Modelling, 99(1), 87-97.

Wildfire in RDDL

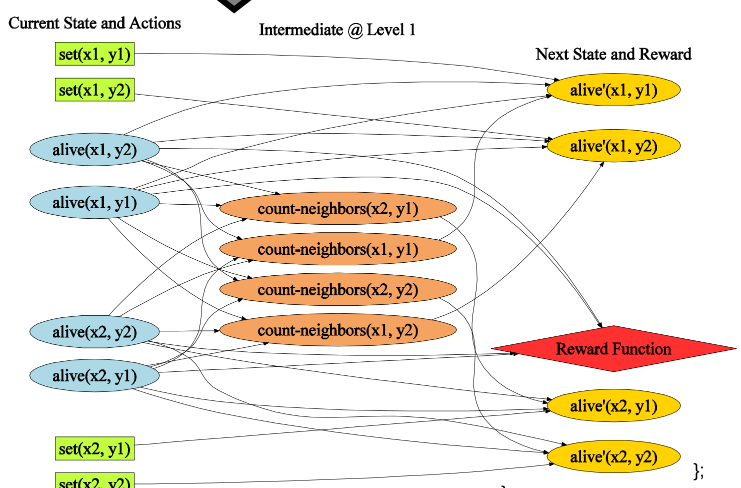
Each cell may independently stochastically ignite

```
cpfs {

      burning'(?x, ?y) =
            if ( put-out(?x, ?y) )
                  then false
            else if (~out-of-fuel(?x, ?y) ^ ~burning(?x, ?y))
                  then Bernoulli( 1.0 / (1.0 + exp[4.5 - (sum_{?x2: x_pos, ?y2: y_pos}
                                              (NEIGHBOR(?x, ?y, ?x2, ?y2) ^ burning(?x2, ?y2)))]) )
            else
                  burning(?x, ?y); // State persists

      out-of-fuel'(?x, ?y) = out-of-fuel(?x, ?y) | burning(?x,?y);

};

reward =
     [sum_{?x: x_pos, ?y: y_pos} [ COST_CUTOUT*cut-out(?x, ?y) ]]
   + [sum_{?x: x_pos, ?y: y_pos} [ COST_PUTOUT*put-out(?x, ?y) ]]
   + [sum_{?x: x_pos, ?y: y_pos} [ COST_NONTARGET_BURN*[ burning(?x, ?y) ^ ~TARGET(?x, ?y) ]]]
   + [sum_{?x: x_pos, ?y: y_pos}
          [ COST_TARGET_BURN*[ (burning(?x, ?y) | out-of-fuel(?x, ?y)) ^ TARGET(?x, ?y) ]]];
```

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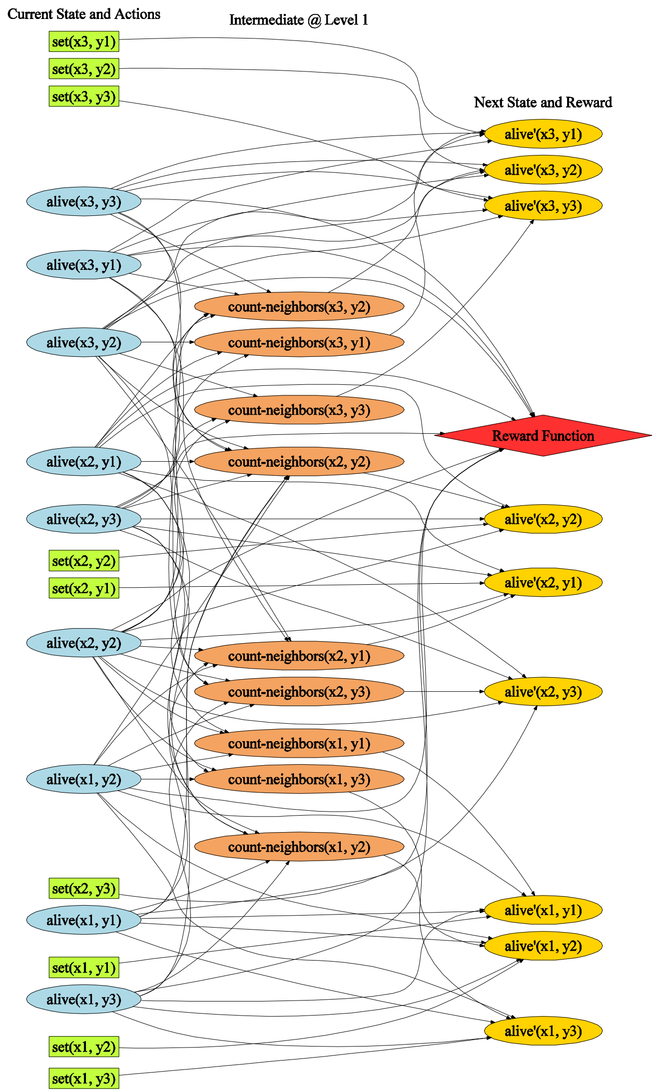
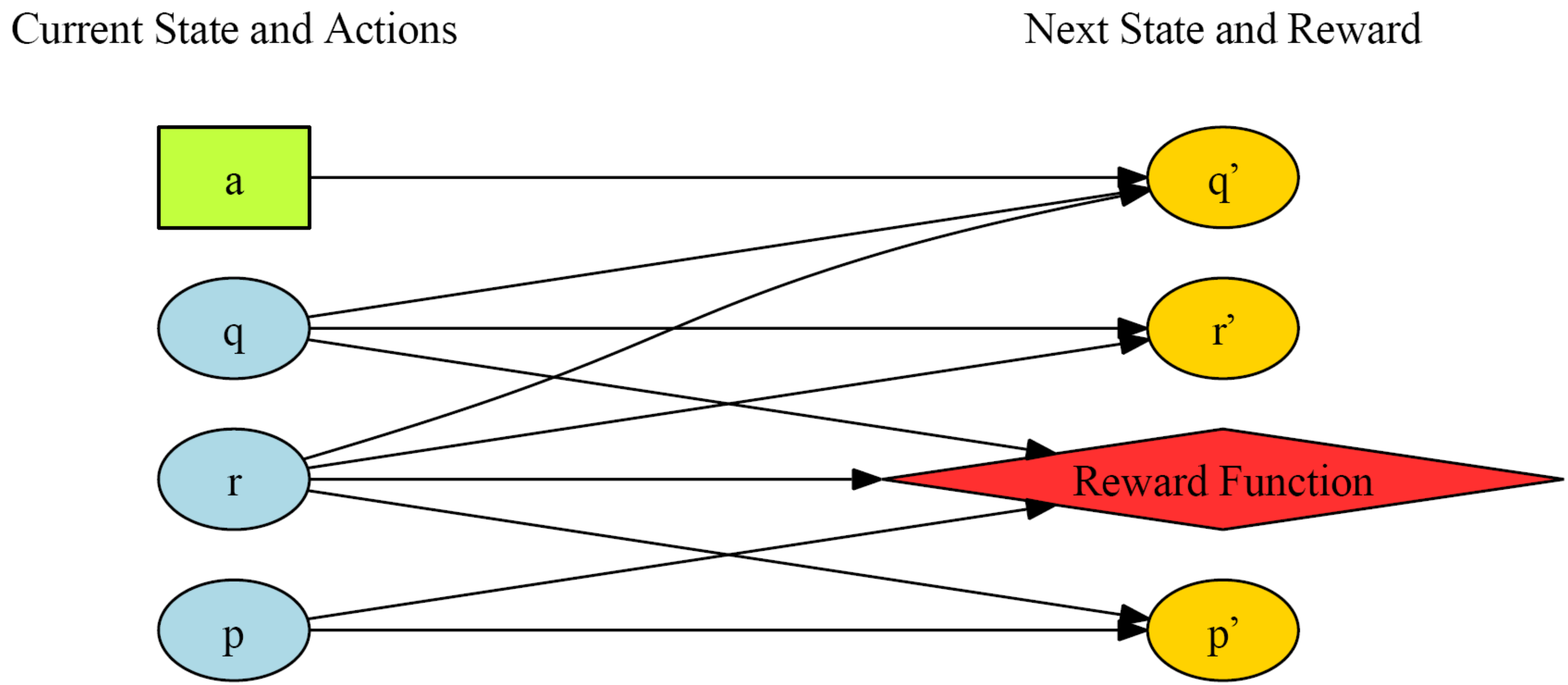



We're getting ahead of ourselves

Let's see how RDDL can specify a binary discrete DBN+ID

How to Represent Factored MDP?



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

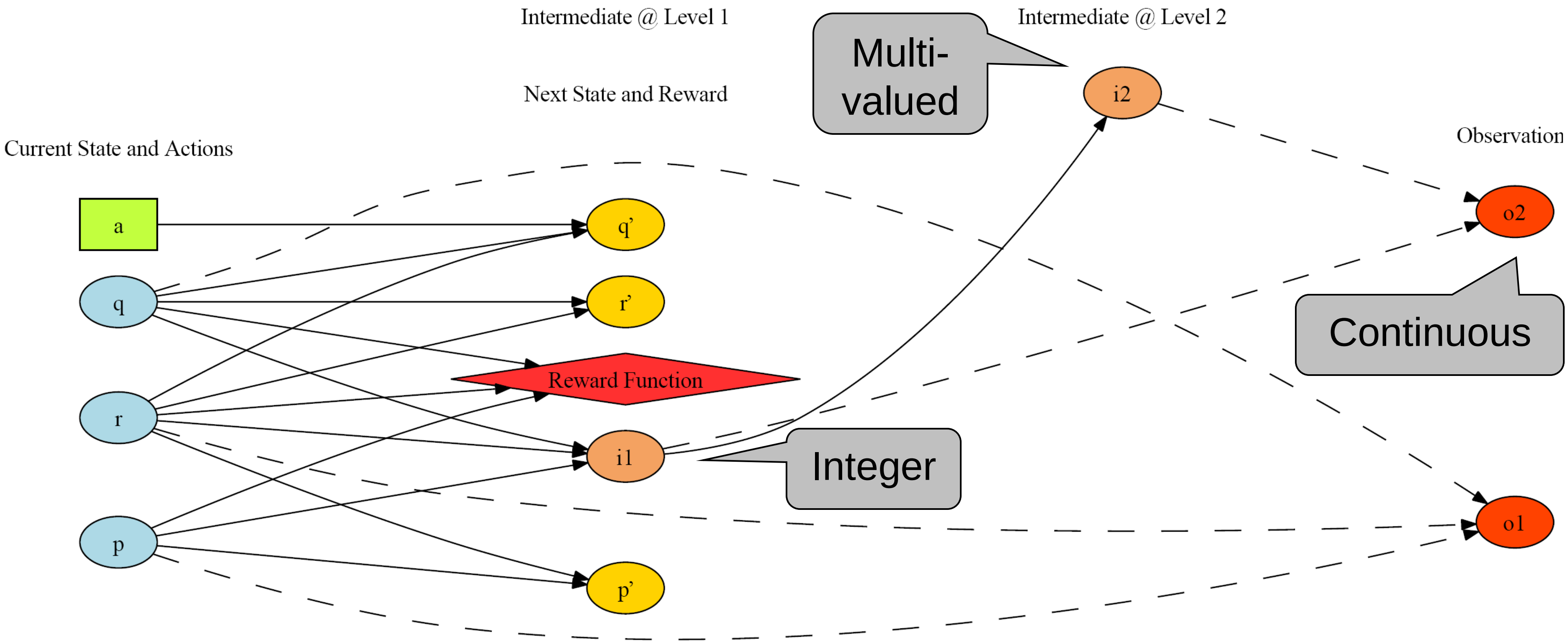
```
// Define the state and action variables (not parameterized here)
pvariables {
    p : { state-fluent,  bool, default = false };
    q : { state-fluent,  bool, default = false };
    r : { state-fluent,  bool, default = false };
    a : { action-fluent, bool, default = false };
};

// Define the conditional probability function for each
// state variable in terms of previous state and actio
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*"

Let's look at a few more RDDL ingredients

- enum, integer, continuous fluents
- intermediate fluents
- observation fluents (POMDP)
- more control / stochastic constructs

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,                    };
    i2 : { interm-fluent, enum_level              };

    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);

// 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
            );
```

Multi-valued

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

Real

```
// 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) };
    };
```

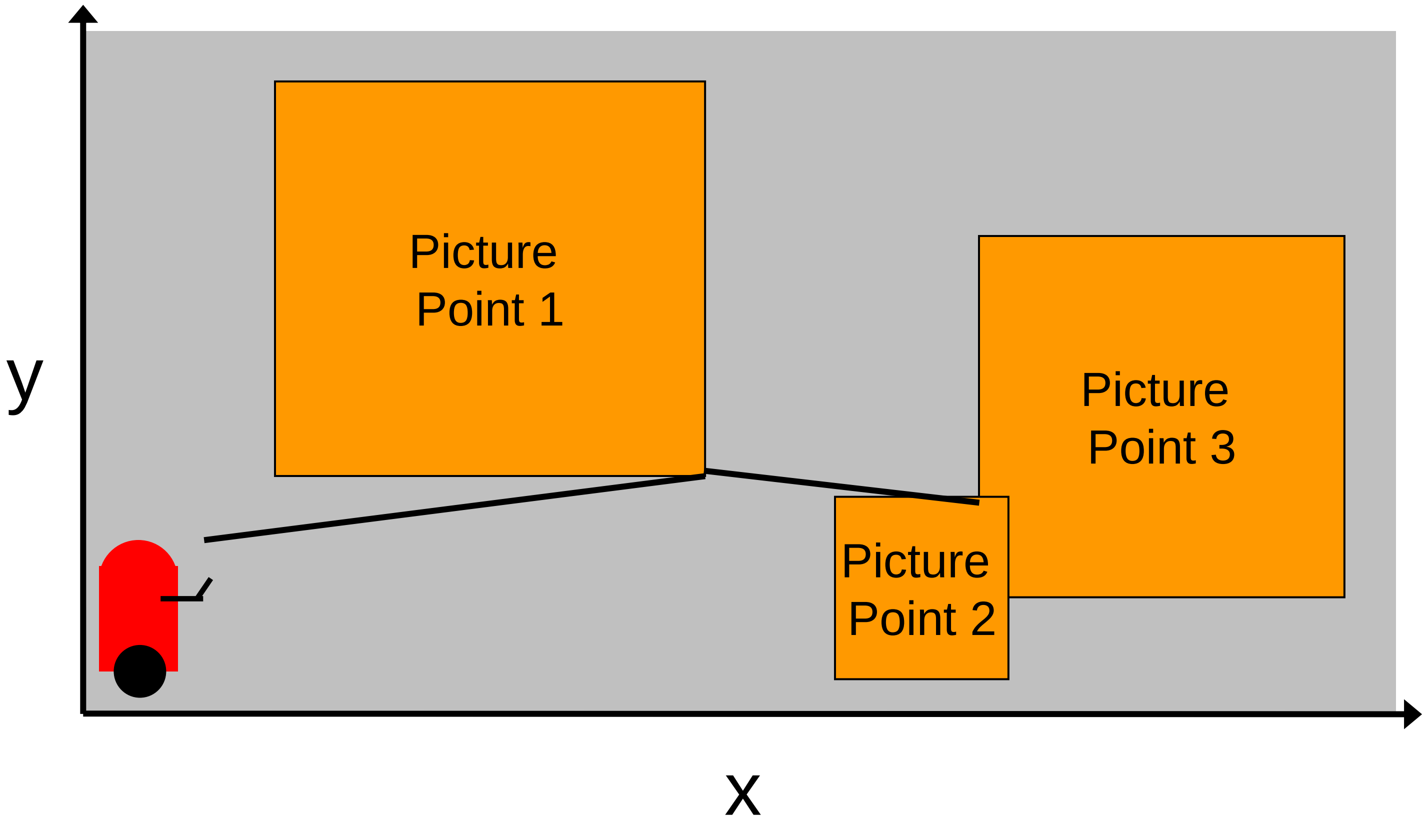
Mixture of Normals

Variance comes from other previously sampled variables

Finally: Mars Rover example

- lifting
- non-fluents
- aggregation expressions
- joint action preconditions

Lifted Continuous MDP in RDDL: **Simple** Mars Rover



Simple Mars Rover: Part I

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

pvariables {

    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 };

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

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

Constant picture points, bounding box

Rover position (only one rover) and time

Rover actions

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 (time + 0.25)
                    else (time + abs[xMove] + abs[yMove]);

};
```

White noise, variance proportional to distance moved

Fixed time for picture

Time proportional to distance moved

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 ((abs[ PICT_XPOS(?p) – xPos] <= PICT_ERROR_ALLOW(?p))
                ^ (abs[ PICT_YPOS(?p) – yPos] <= PICT_ERROR_ALLOW(?p)))
             then PICT_VALUE(?p)
             else 0.0 ]
            else 0.0;
```

Reward for all pictures taken within bounding box!

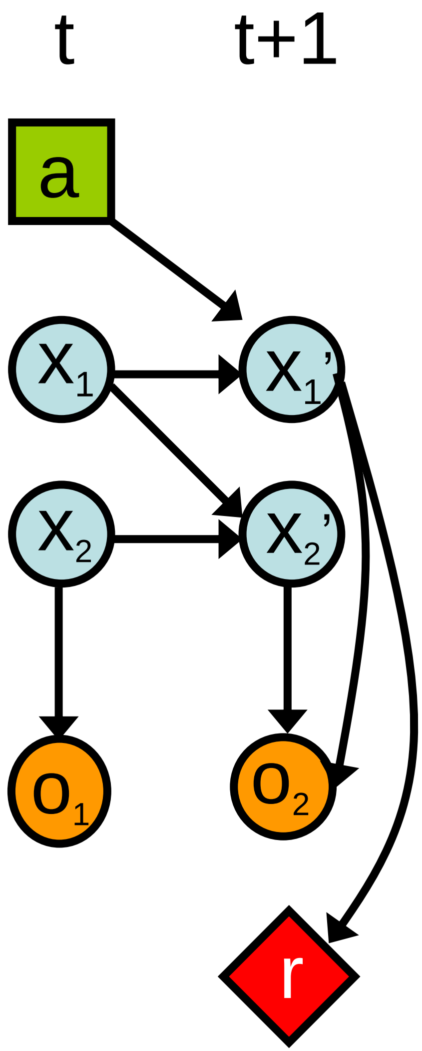
```
action-preconditions {

        // 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.

RDDL Recap

- Relational Dynamic Influence Diagram Language
  - Relational [DBN + Influence Diagram]

- Specify the probabilistic process over relations to generate next state
  - Generate “ground” DBN+ID given domain object instantiation



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
  - Naturally supports independent exogenous events

- General expressions in transition / reward
  - Logical expressions ($\wedge$, $\vee$, $\Rightarrow$, $\Leftrightarrow$, $\forall$, $\exists$)
  - Arithmetic expressions (+,−,*, /, $\sum_x$, $\prod_x$)
  - In/dis/equality comparison expressions (=, $\neq$, <,>, $\leq$, $\geq$)
  - Conditional expressions (if-then-else, switch)
  - Standard Functions: pow[.], log[.], abs[.], max[.], sin[.]
  - Basic probability distributions
    - Bernoulli, Discrete, Normal, Poisson

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

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 action-preconditions
    - (concurrent) action preconditions
  - Assert state-invariants
    - serve as integrity constraint checks on state
    - e.g., an elevator cannot be in two locations

What RDDL does not do…

- RDDL just provides a language for specifying complex (PO)MDPs
  - For an MDP: <S, A, T, R>
  - For a POMDP: <S, A, T, R, O, Z>

- RDDL does not define a policy
- RDDL does not specify a planning methodology
  - It's up to **external planners** to perform planning, learning, or inference on the RDDL domain model

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  - **Overview of RDDL solution methodologies**

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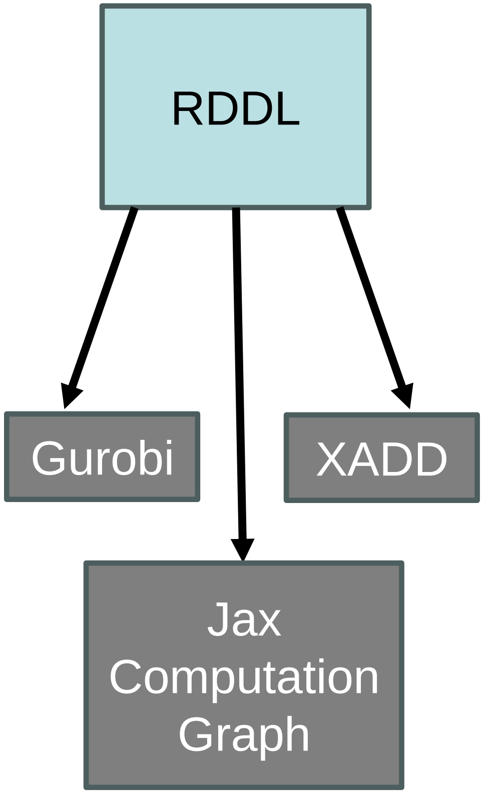
Common question from RL crowd: Why RDDL vs. a Simulator in C++?

Answer: Want a language that can be **compiled** into other formalisms for planning and domain analysis such as abstraction.

RDDL is a disciplined subset of modern languages designed to facilitate compilation.



RDDL Planning Overview

- SOTA: **compile instance** to planning formalism
  - MCTS (Discrete Search) (PROST, Keller et al, ICAPS-12) – discrete only
  - Symbolic Methods (Decision Diagrams – XADDs)
  - Planning by Backprop (Tensorplan, JaxPlan, SOGBOFA)
  - Planning by Optimization in Gurobi (Raghavan et al, AAAI-17)

- Generalized Planning: “solve” at **lifted domain** level
  - Relational / First-order MDPs (Khardon et al, Sanner et al)
  - Graph neural network policies (Symnet 1/2/3: Mausam et al)
  - Plan / policy should work for all instances

Symbolic Decision Diagram Methods

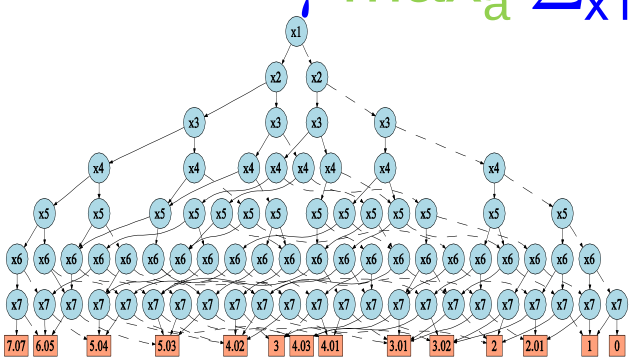
SPUDD for Factored MDPs

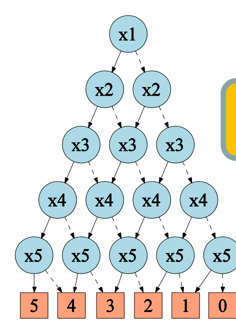
- Value Iteration using ADDs (SPUDD)
  - Can use ADDs or any DD that supports +,*,max
  - Bounded approximations (APRICODD)

DD DD DD DD

$$V^{n+1}(x_1 \ldots x_i) = R(x_1 \ldots x_i) + \gamma \cdot \max_a \sum_{x1' \ldots xi'} \prod_{F1 \ldots Fi} P(x_1' | \ldots x_i) \ldots P(x_i' | \ldots x_i) \, V^n(x_1' \ldots x_i')$$

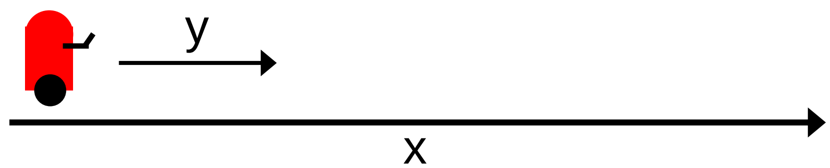
DD

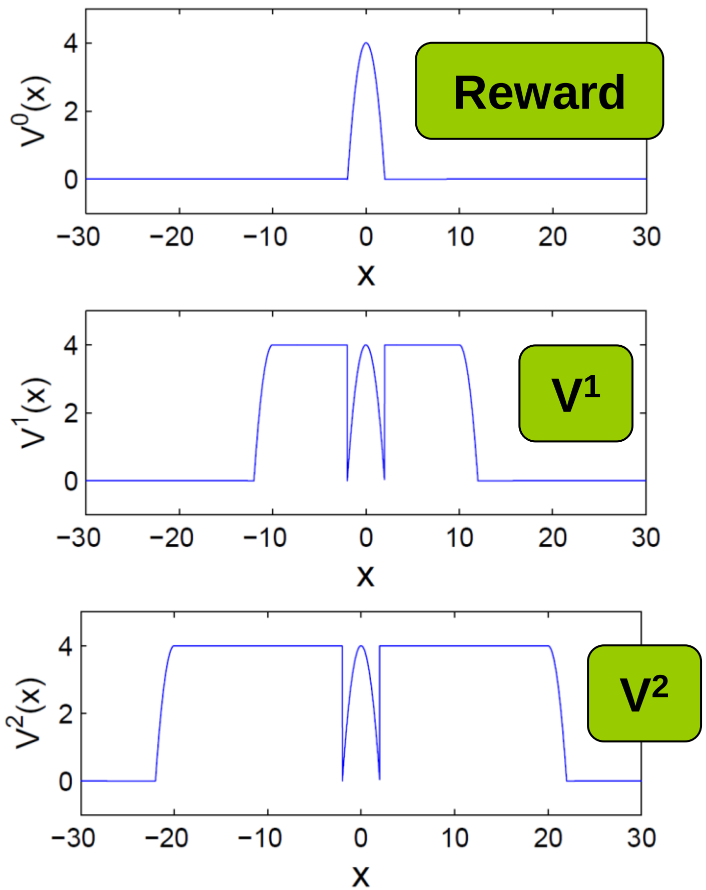


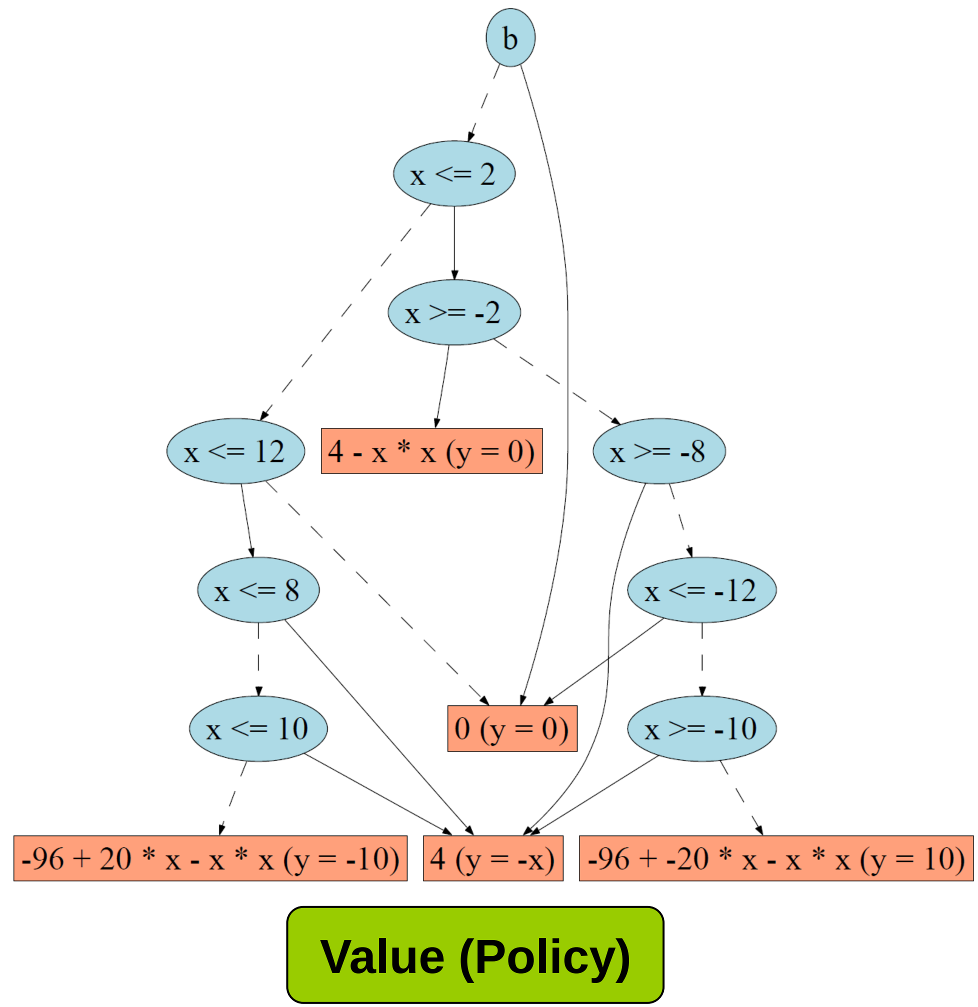


Sanner et al (UAI-11, AAAI-12, UAI-13)

XADDs for Discrete+Continuous MDPs





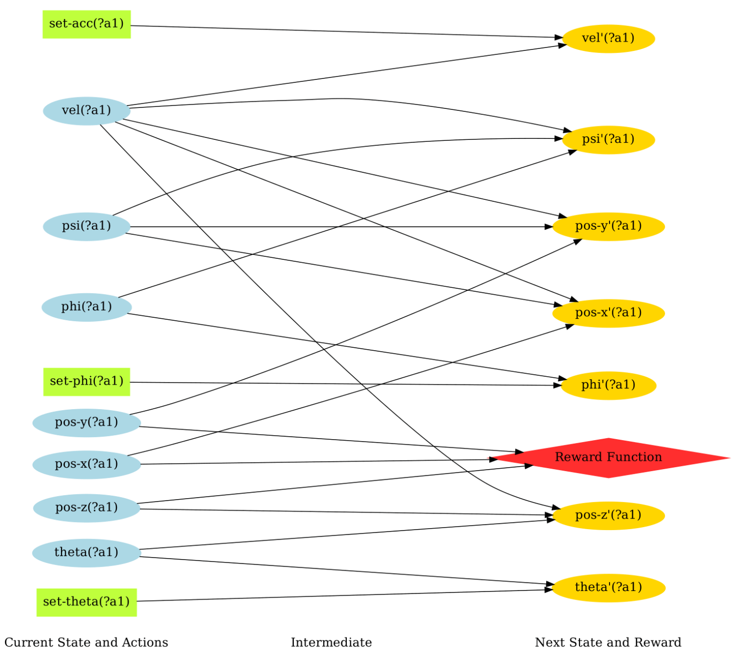


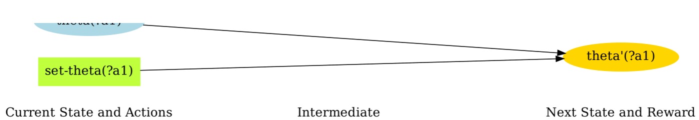
https://ataitler.github.io/IPPC2023/xadd.html

RDDL Compiles to (X)ADDs!

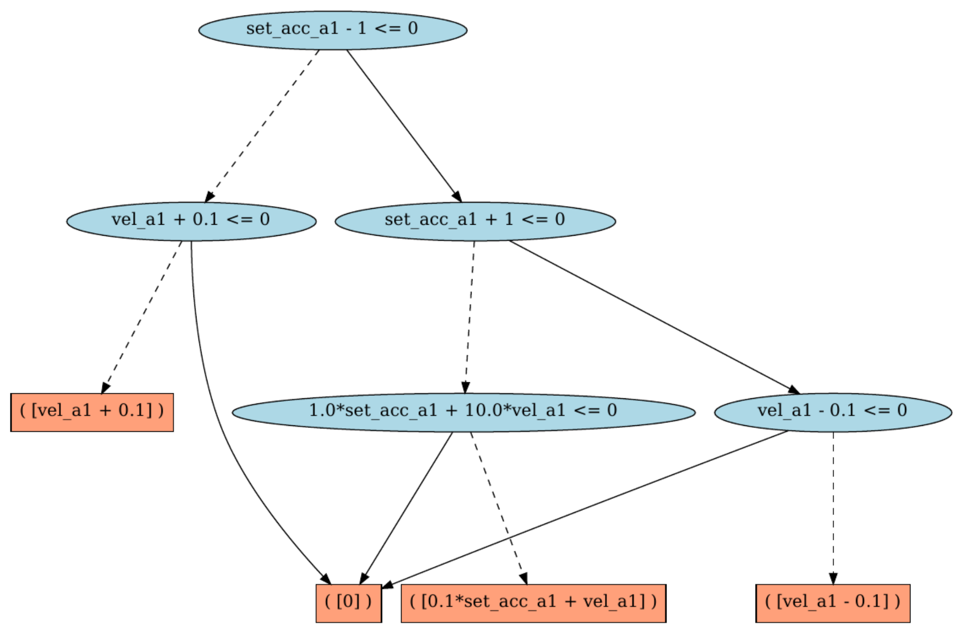
- UAV Problem

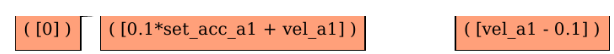
DBN





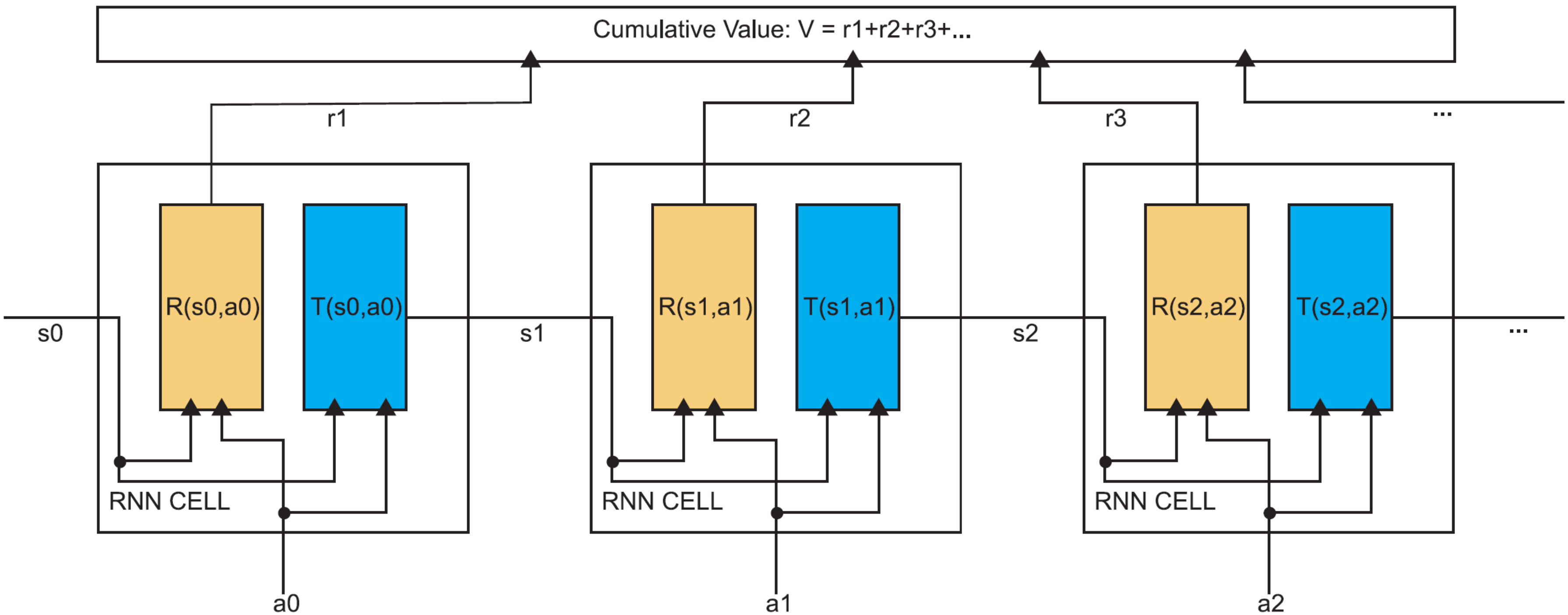
XADD for vel'(a1)





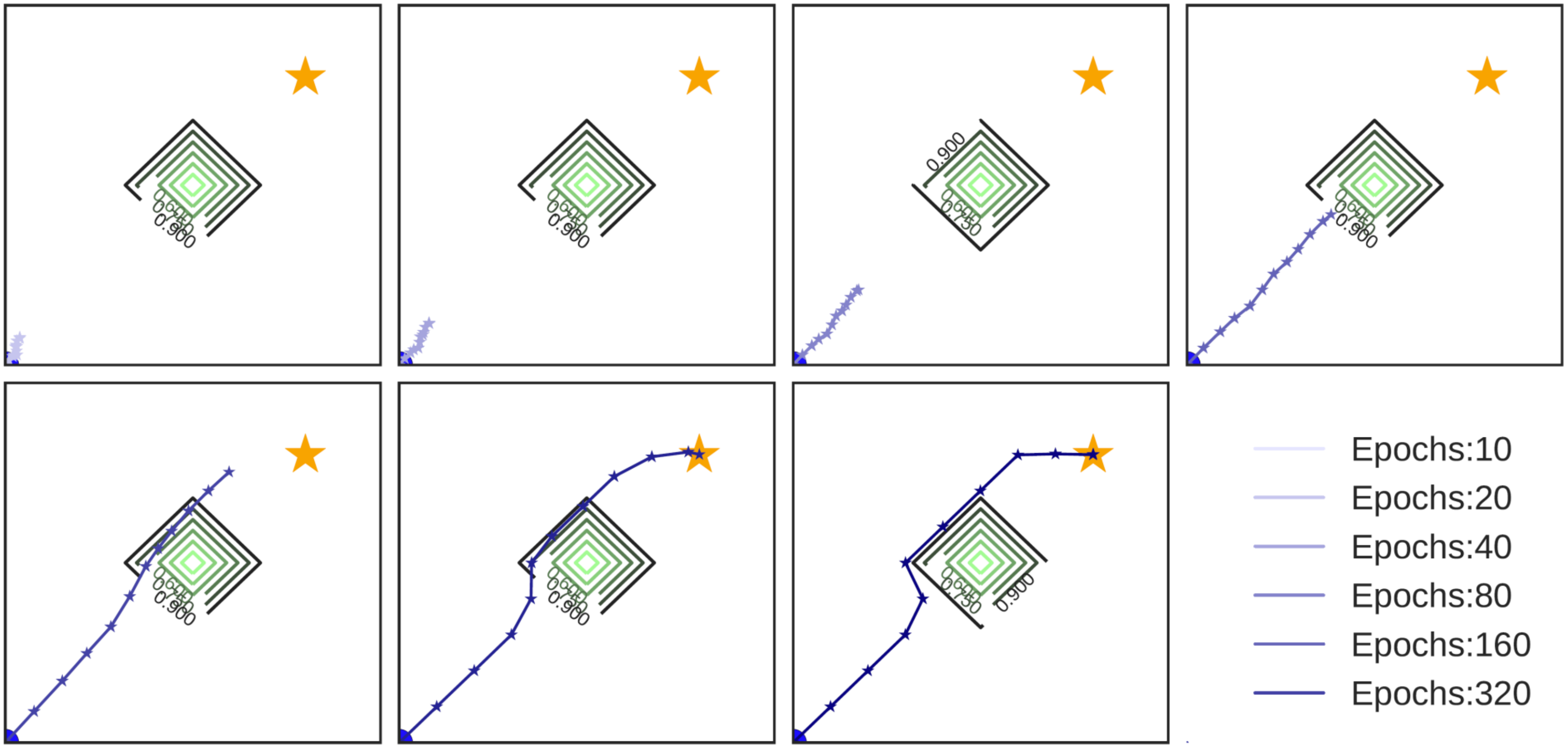
Planning by Backprop

Tensorplan: Embed Reward and Transition in an RNN and Optimize *End-to-end*!



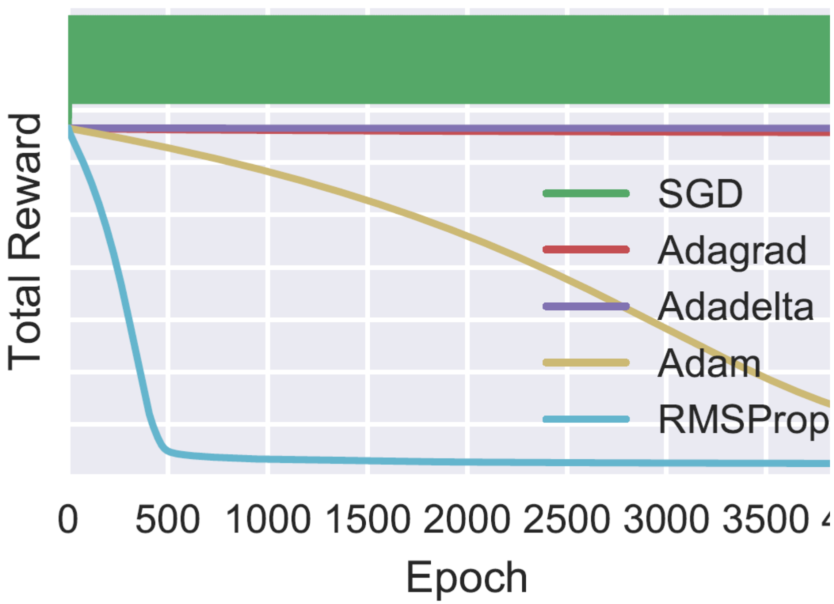
GPU-based Path Planning via Tensorflow

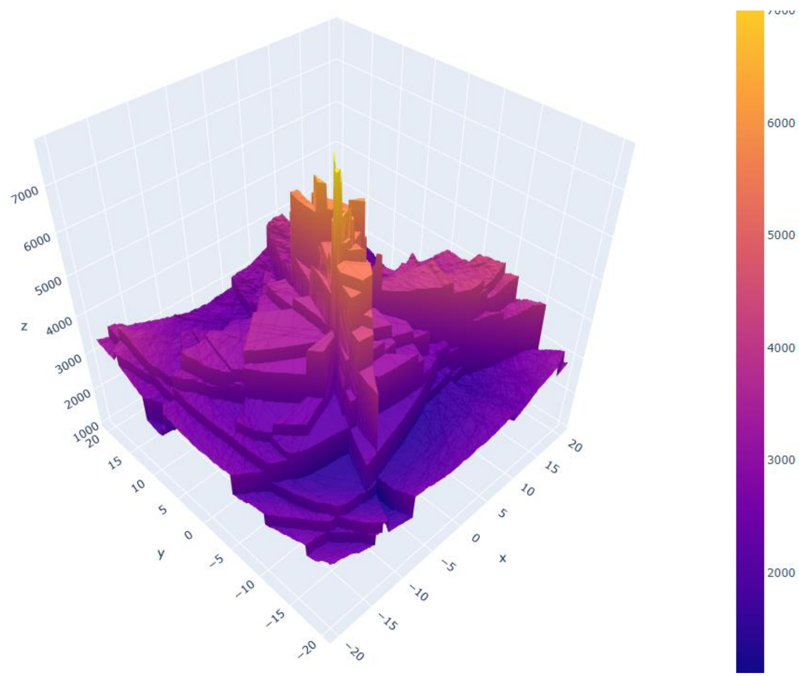
- RMSProp makes for a great non-convex optimizer!



JaxPlanner for RDDL: https://pyrddlgym.readthedocs.io/en/latest/advanced.html#open-loop-planning-with-jax

Need Modern Non-convex Gradient Methods



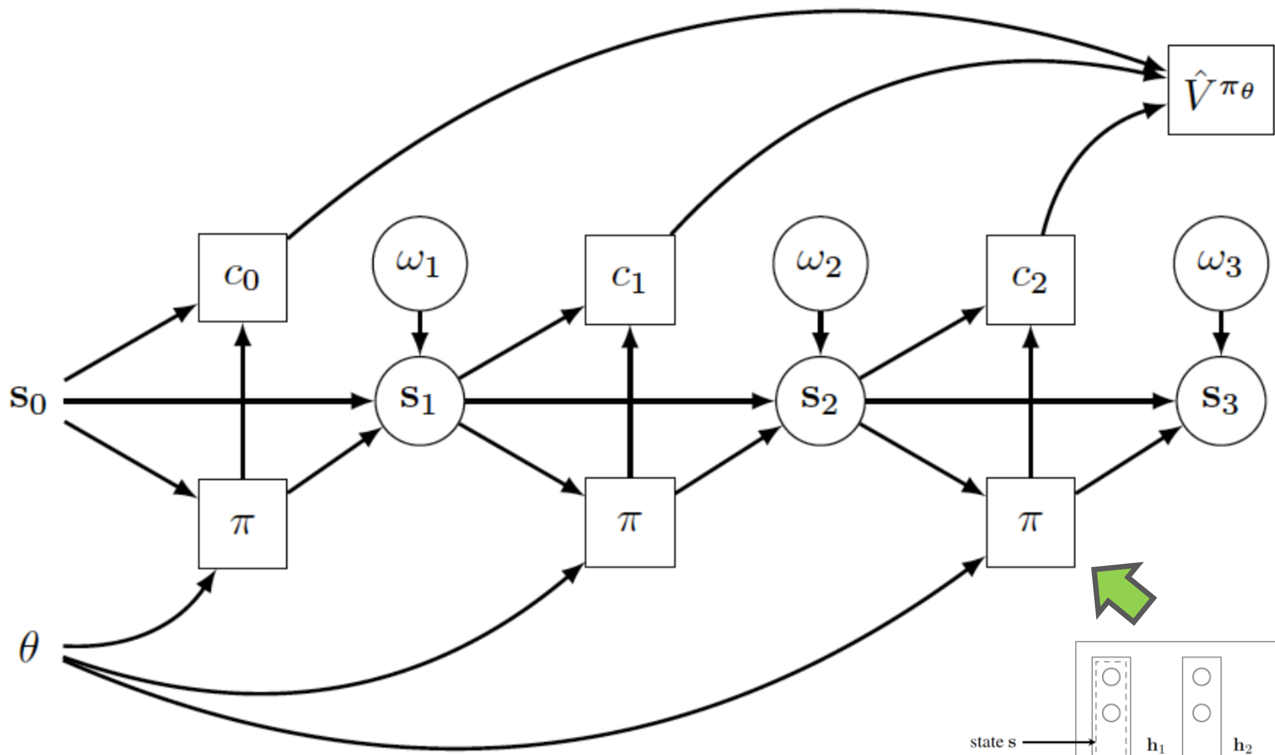


RMSProp is the best-performing optimizer for planning, likely b/c it can handle piecewise structure.

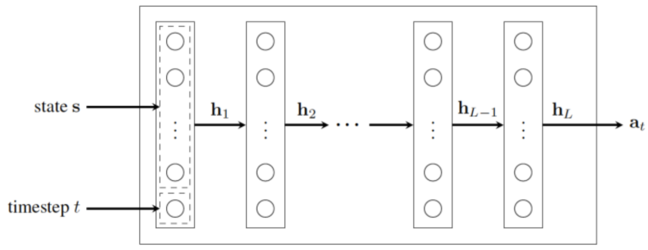
Bueno, …, Sanner (AAAI-19)

Learning Deep Reactive Policies (DRPs)

Stochastic RNNs



DRP

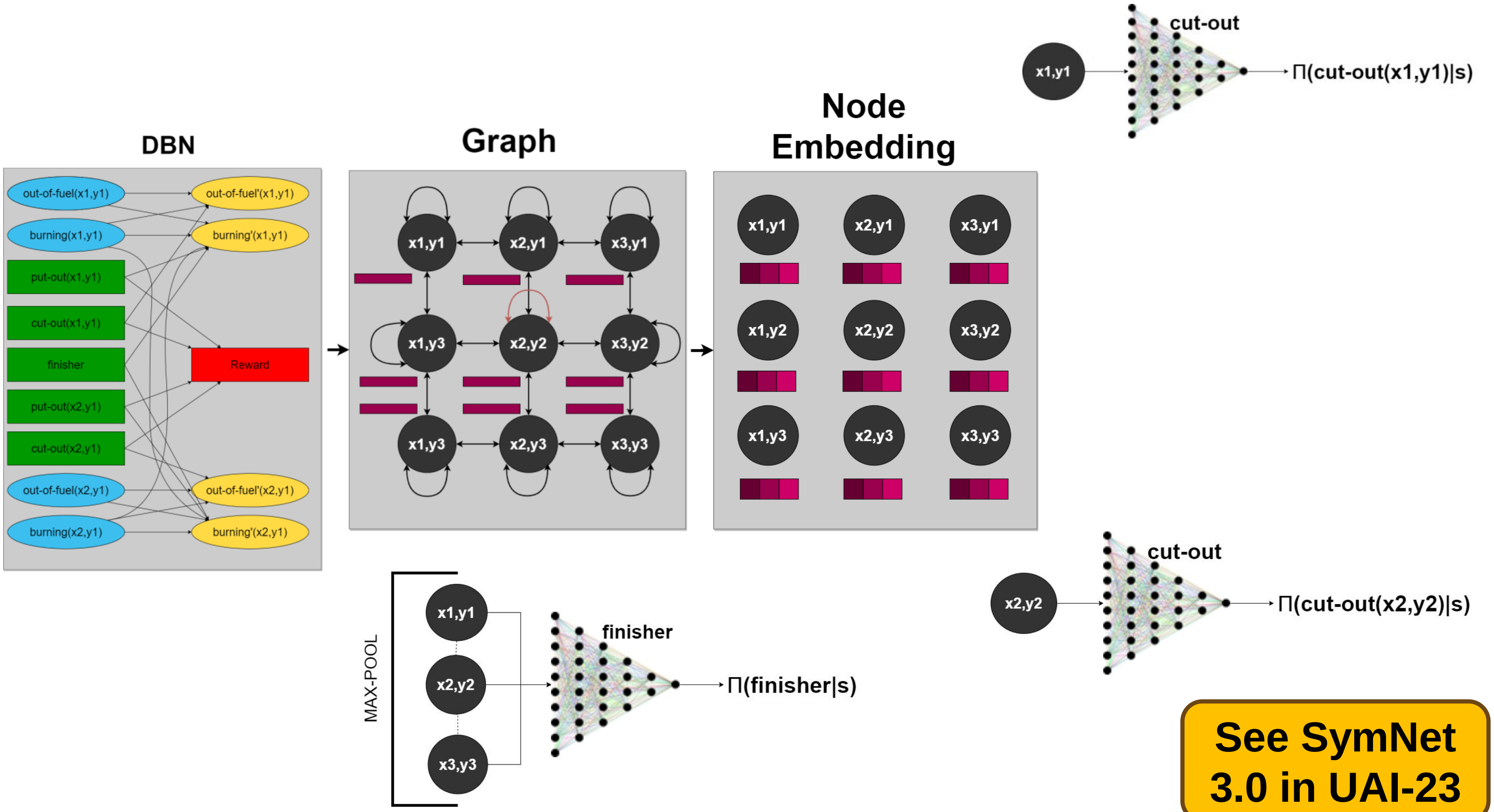


Lifted Approaches: Generalized Planning for RDDL

SymNet (Mausam and students)

SymNet 2.0 (Mausam et al, ICML-22)

Compile RDDL DBN into GNN, Embed, Decode to Actions
(GNN learning is domain instance indepencent)



See SymNet 3.0 in UAI-23

RDDL Tutorial Outline

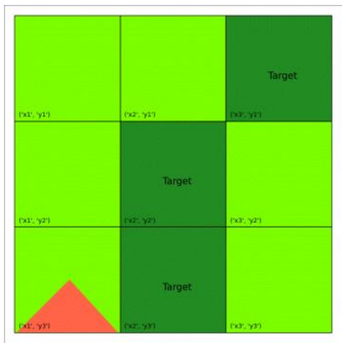
- Part 1: Language Overview
  - What is probabilistic planning in PPDDL?
  - Why do we need RDDL?
  - RDDL by example
  - Overview of RDDL solution methodologies

- **Part 2: PyRDDLGym**

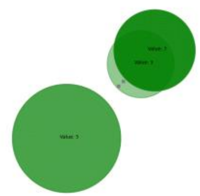
pyRDDLGym

Includes OpenAI Gym interface, JaxPlanner, XADDs, etc.
https://github.com/ataitler/pyRDDLGym

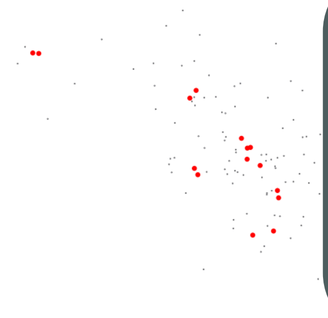
More on PyRDDLGym with worked examples in Part 2!



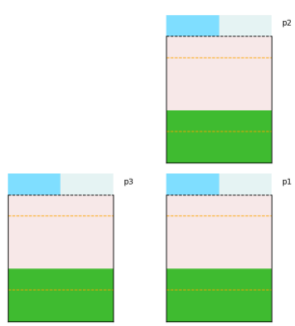
Wildfires



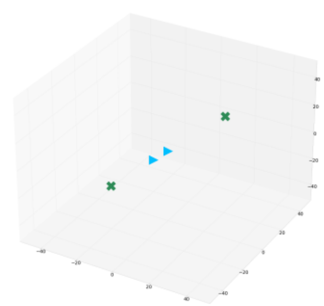
Mars Rover



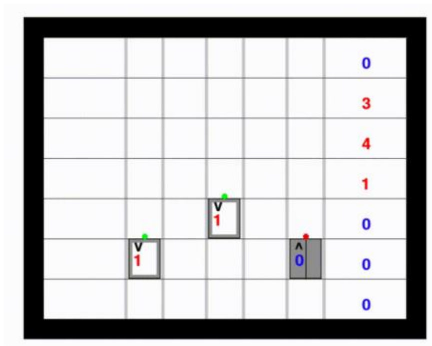
Recommender System



Power Generation



UAVs



Elevators