Towards Comprehensible representation of controllers using Machine Learning: Inductive Logic Programming

Under Prof. Dr. Jan Křetínský

As part of my summer internship
(DAAD)
at
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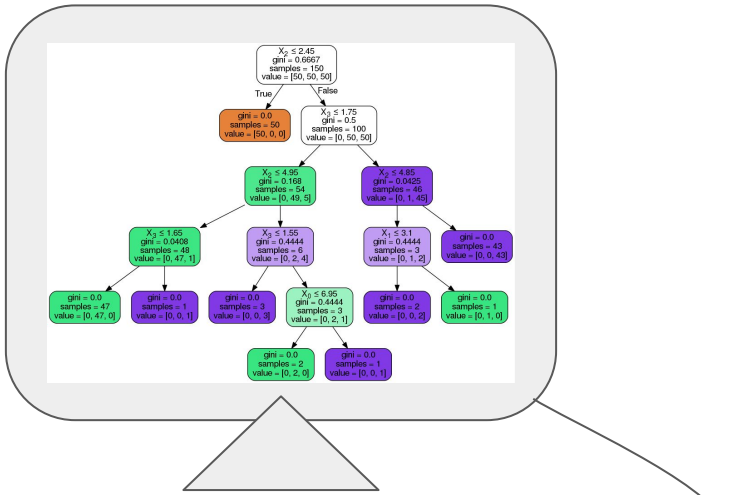
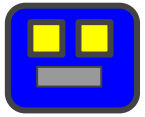


- **Comprehensible representation of controllers**
  - What are they?
  - Model Checking??
  - MDPS???
- **Machine Learning**
  - Decision Trees
  - Inductive Logic Programming....

Towards Comprehensible representation of **controllers** using Machine Learning: Inductive Logic Programming

Real Life System + Specifications

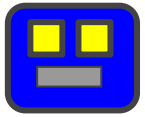


Safety is critical

Testing, Validation..

Write code manually and test

Real Life System + Specifications



Safety is critical

Testing, Validation..

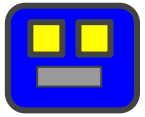
Model Checker (Model + Properties)

Controller Strategy

.
.
.
.
.

Write code manually and test
OR
Mathematically model the system and its properties (requirements) and feed it to a model checker.

Real Life System + Specifications



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.
.
.
.
.

Write code manually and test
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The strategy i.e. the logic of the software which is to be followed by the physical system.

Controller Strategy

.

.

.

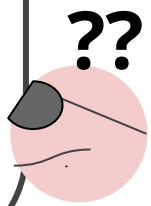
.

.

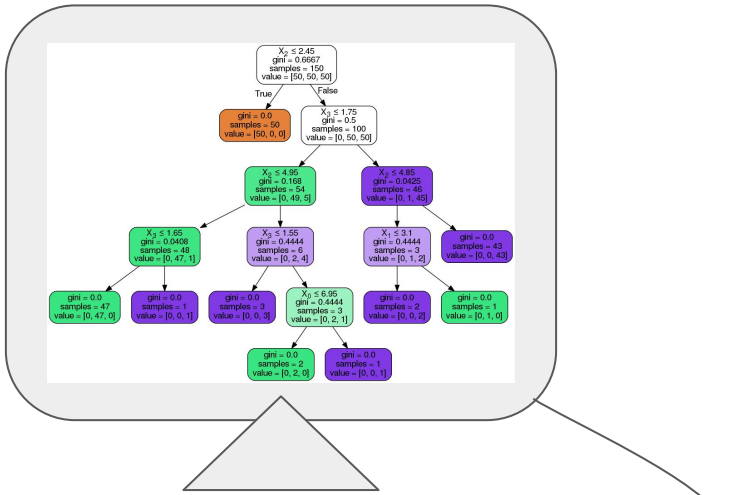

Controller
Strategy

State 1: Action(s) allowed
State 2: Action(s) allowed
State 3: Action(s) allowed
.
.
.
.
.
.
..

State 1: Action(s) allowed
State 2: Action(s) allowed
State 3: Action(s) allowed



Towards **Comprehensible representation** of controllers using Machine Learning: Inductive Logic Programming



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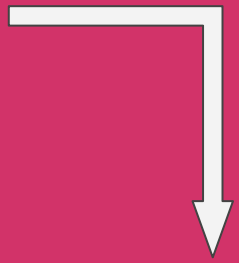
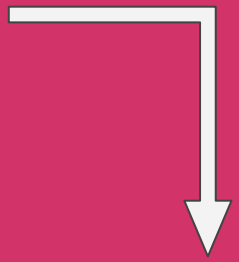
- **Machine Learning**
  - Decision Trees
  - Inductive Logic Programming....

Towards Comprehensible representation of controllers using **Machine Learning**: Inductive Logic Programming

Input: Sample data

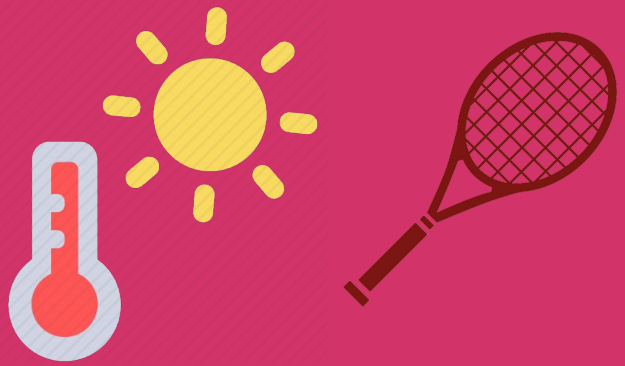


Build a model



Predict on unseen data

Input: Sample data



Build a model

Predict on unseen data

Input: Sample data

Build a model

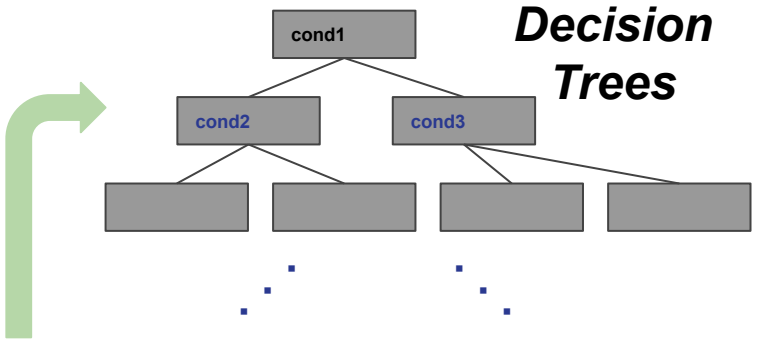
??

Predict on unseen data

AIM:
Why ML at all?

- Learn a strategy and represent (predict)
- In a much smaller form
- Capture the most essential decisions of a strategy
- While not compromising on safety, i.e. not predicting spuriously.

Build a *model:*
Previous work



Decision Trees

Controller Strategy

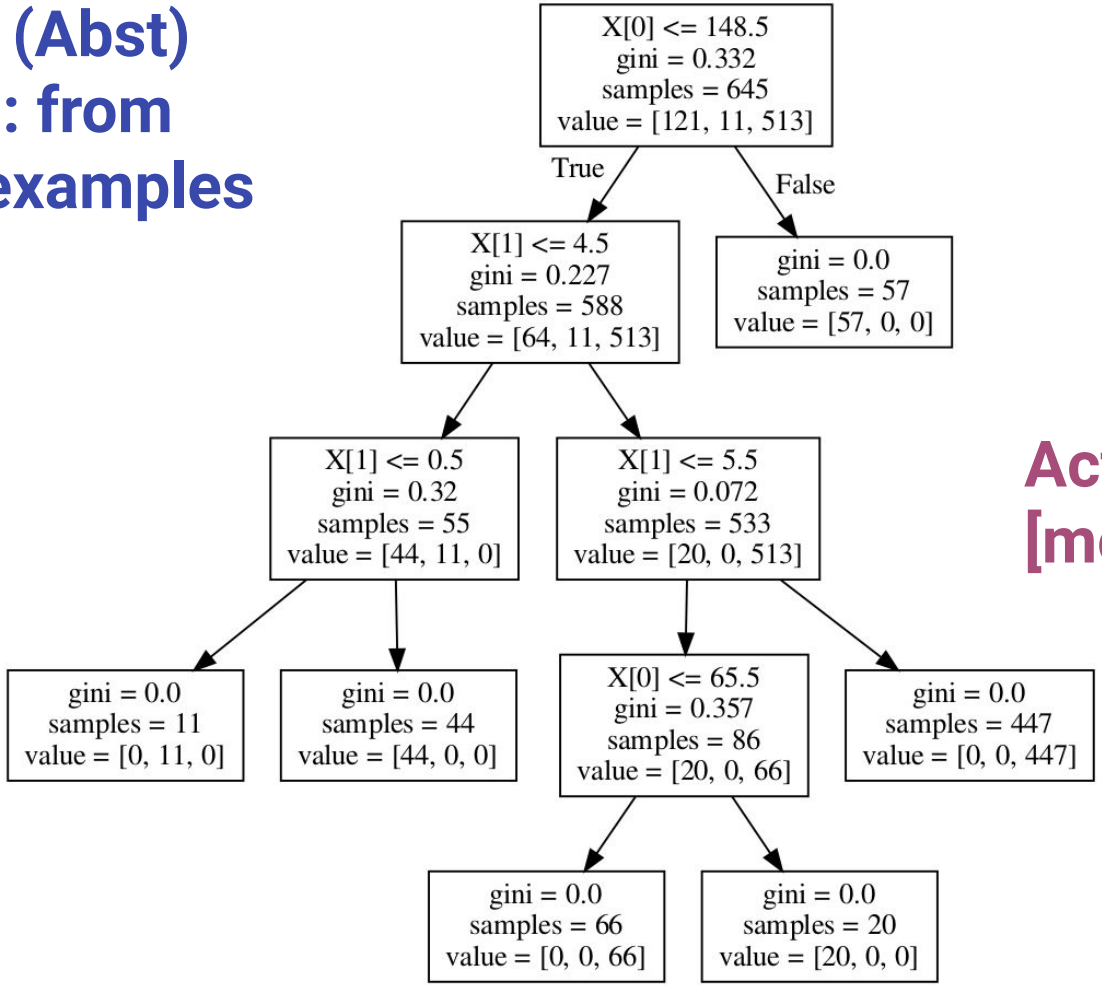
??

Machine Learning

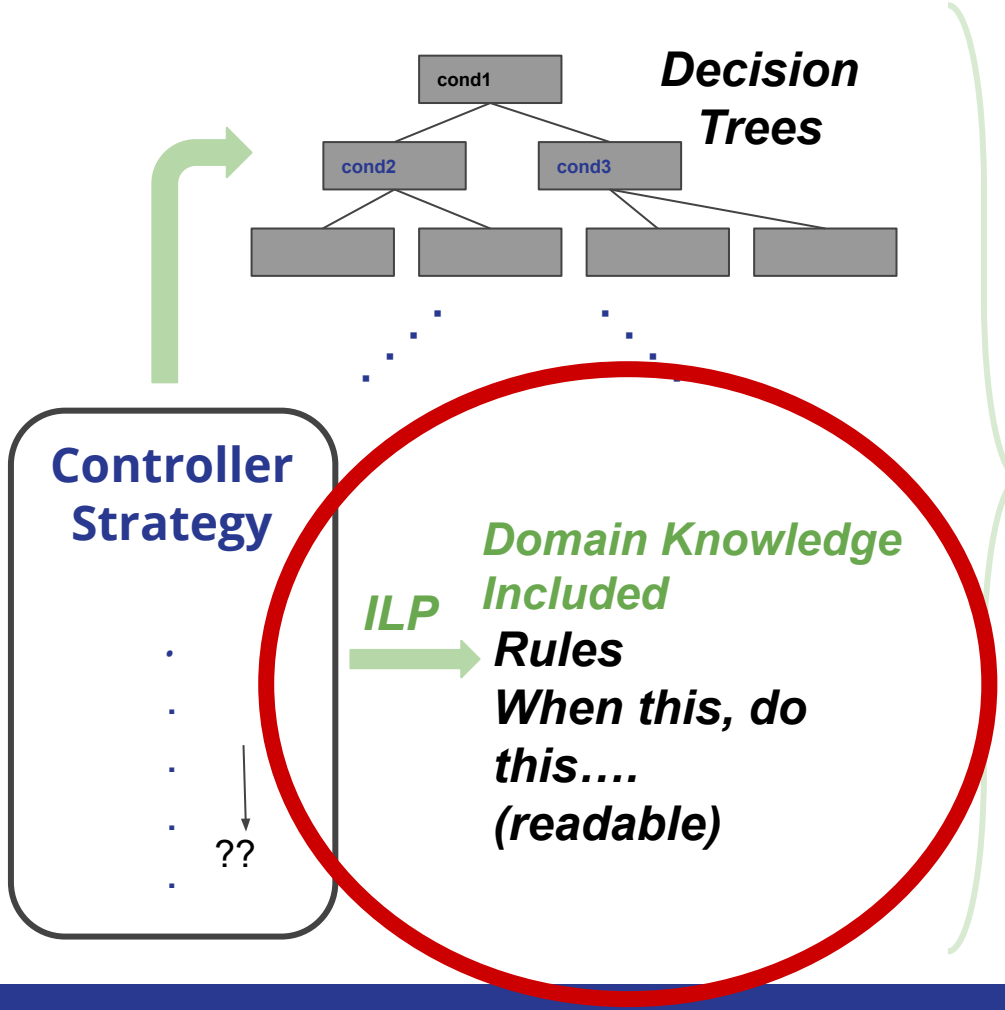
- MDPs
- Stochastic Hybrid Games
- Graph Games

Firewire (Abst) Dataset : from PRISM examples

X[0] : x
X[1] : s



Actions: [move,round,time]



Now our model is Inductive Logic Programming

Towards Comprehensible representation of controllers using Machine Learning: **Inductive Logic Programming**

For Starters :
Inductive Logic Programming

Deductive vs Inductive?

Hypothesis: All Girls are Smart

Deductive vs Inductive?

Hypothesis: All Girls are Smart

and

Jill is a girl

Deductive vs Inductive?

Hypothesis: All Girls are Smart

and

Jill is a girl

Jill is smart

Deductive vs Inductive?

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and

Jill is a girl

Jill is smart

DEDUCTIVE

Deducing ***Specific*** details
from ***General*** Hypothesis

Deductive vs Inductive?

Jill is smart

Deductive vs Inductive?

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and

Jill is a girl

Deductive vs Inductive?

Jill is smart

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Hypothesis: All Girls are Smart

Deductive vs Inductive?

Jill is smart

and

Jill is a girl

Hypothesis: All Girls are Smart

INDUCTIVE

"Inducing" ***General*** hypothesis from ***Specific*** Details

Indeed, Machine Learning in some sense..

For Starters: ILP

What we have :

1. Background Knowledge (B)
2. Set of Positive Examples (E+)
3. Set of Negative Examples (E-)

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What we want:

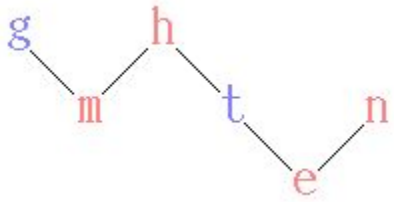
A Hypothesis which is ***"good"***:

-> Maximises the number of positive examples satisfied

-> Does NOT satisfy any negative examples

-> Has literals in the body as less as possible

For Starters: *ILP*



par: *parent*, *fem*: *female*, *dau*: *daughter*, *g*: *George*, *h*: *Helen*, *m*: *Mary*, *t*: *Tom*, *n*: *Nancy*, and *e*: *Eve*.

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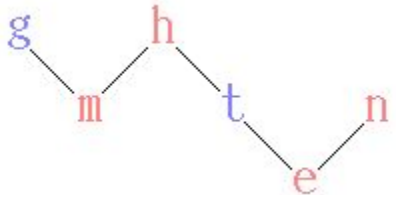

par: *parent*, *fem*: *female*, *dau*: *daughter*, *g*: *George*, *h*: *Helen*, *m*: *Mary*, *t*: *Tom*, *n*: *Nancy*, and *e*: *Eve*.

$$par(h,m) \wedge par(h,t) \wedge par(g,m) \wedge par(t,e) \wedge par(n,e) \wedge fem(h) \wedge fem(m) \wedge fem(n) \wedge fem(e),$$

What we have :

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$$dau(m,h) \wedge dau(e,t),$$

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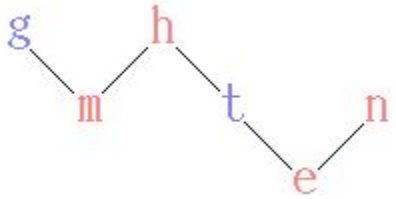

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$$par(h,m) \wedge par(h,t) \wedge par(g,m) \wedge par(t,e) \wedge par(n,e) \wedge fem(h) \wedge fem(m) \wedge fem(n) \wedge fem(e),$$

What we have :

1. Background Knowledge (B)
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3. Set of Negative Examples (E-)

$$dau(m,h) \wedge dau(e,t),$$

What we want:

A Hypothesis which is ***"good"***:

$$dau(x_{me}, x_{ht}) \leftarrow par(x_{ht}, x_{me}) \wedge fem(x_{me})$$

-> Maximises the number of positive examples satisfied

-> Does NOT satisfy any negative examples

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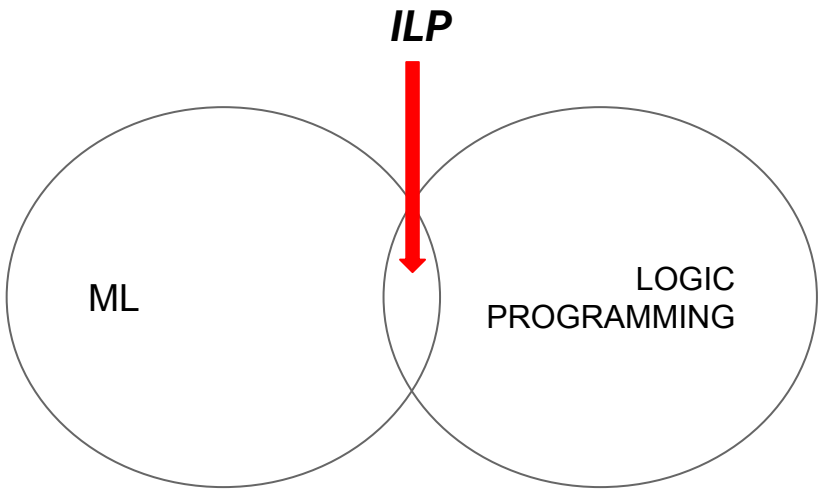
For Starters: *ILP*



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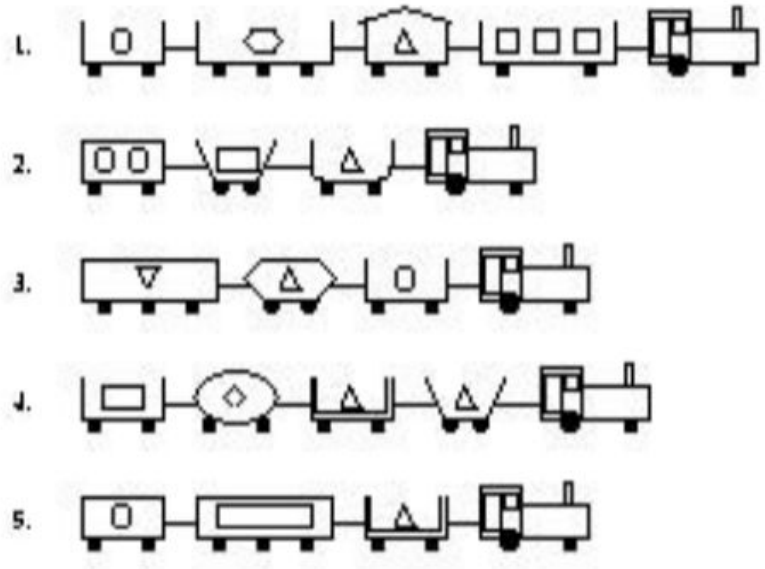
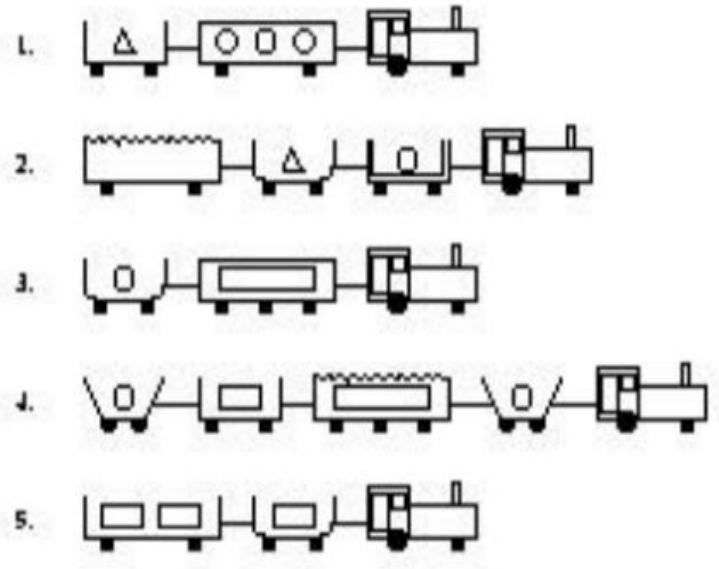
EXAMPLES

TRAINS





```
car(car_51).  car(car_52).  car(car_53).
car(car_61).  car(car_62).
car(car_71).  car(car_72).  car(car_73).
car(car_81).  car(car_82).
car(car_91).  car(car_92).  car(car_93).  car(car_94).
car(car_101).  car(car_102).

shape(elipse).  shape(hexagon).  shape(rectangle).  shape(u_shaped).
shape(triangle). shape(circle). shape(nil).

train(east1).  train(east2).  train(east3).  train(east4).  train(east5).
train(west6).  train(west7).  train(west8).  train(west9).  train(west10).


% eastbound train 1
short(car_12).      % 0
closed(car_12).     % 1
long(car_11).       % 2
long(car_13).
short(car_14).
open_car(car_11).       % 3
open_car(car_13).
open_car(car_14).
shape(car_11,rectangle). % 4,5
shape(car_12,rectangle).
shape(car_13,rectangle).
shape(car_14,rectangle).
load(car_11,rectangle,3). % 6,7,8
load(car_12,triangle,1).
load(car_13,hexagon,1).
load(car_14,circle,1).
wheels(car_11,2).     % 9,10
wheels(car_12,2).
wheels(car_13,3).
wheels(car_14,2).
has_car(east1,car_11). % 11,12
has_car(east1,car_12).
has_car(east1,car_13).
```

B

```
eastbound(east1).
eastbound(east2).
eastbound(east3).
eastbound(east4).
eastbound(east5).
```

E+

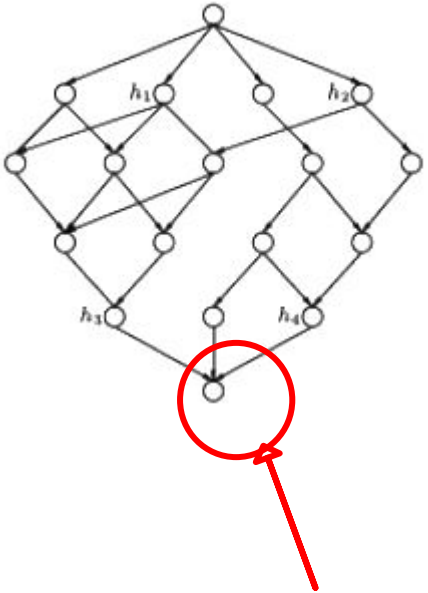
```
eastbound(west6).
eastbound(west7).
eastbound(west8).
eastbound(west9).
eastbound(west10).
```

E−

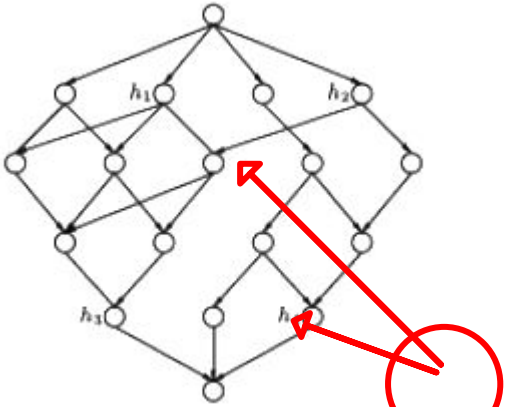
```
eastbound(A) :-
   has_car(A,B), has_car(A,C), has_car(A,D), has_car(A,E),
   short(E), short(C), closed(C), long(D),
   long(B), open_car(E), open_car(D), open_car(B),
   shape(E,rectangle), shape(D,rectangle), shape(C,rectangle), shape(B,rectangle),
   wheels(E,2), wheels(D,3), wheels(C,2), wheels(B,2),
   load(E,circle,1), load(D,hexagon,1), load(C,triangle,1), load(B,rectangle,3).
```

A general hypothesis about eastbound trains, given the background knowledge and positive and negative instances

Greedy search along the lattice of hypothesis

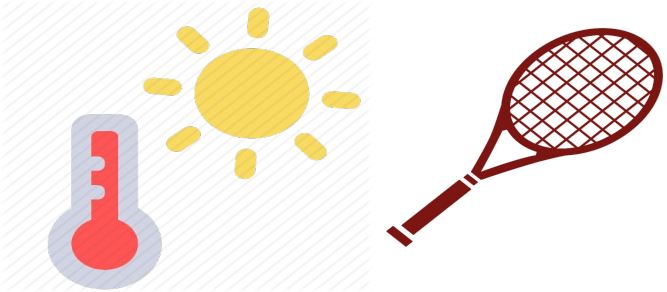


Most Specific Hypothesis (MSH) for a positive example e



More General Hypotheses

To play or not to play



```
[Rule 1] [Pos cover = 2 Neg cover = 0]
class(A,B) :-
   not (outlook(A,rain),windy(A,true)), outlook(A,sunny), humidity(A,C), lteq(C,70),
   random(B,[0.75-play,0.25-dont_play]).

[Rule 2] [Pos cover = 3 Neg cover = 0]
class(A,B) :-
   not (outlook(A,rain),windy(A,true)), outlook(A,sunny), not (humidity(A,C),lteq(C,70)), random(
   B,[0.8-dont_play,0.2-play]).

[Rule 3] [Pos cover = 7 Neg cover = 0]
class(A,B) :-
   not (outlook(A,rain),windy(A,true)), not outlook(A,sunny), random(B,[0.888889-play,0.111111-dont_play]).

[Rule 4] [Pos cover = 2 Neg cover = 0]
class(A,B) :-
   outlook(A,rain), windy(A,true), random(B,[0.75-dont_play,0.25-play]).
```

In the context of strategies..

Cruise Control

Ego

Ego is controlled by us

Front

Front is environment controlled : "given to us"

The goal of the adaptive cruise control in Ego is

1. To stay safe (by keeping the distance between the cars greater than a given safe distance) ***SAFETY***

2. To drive as close to Front as possible. ***OPTIMALITY***

Cruise Control

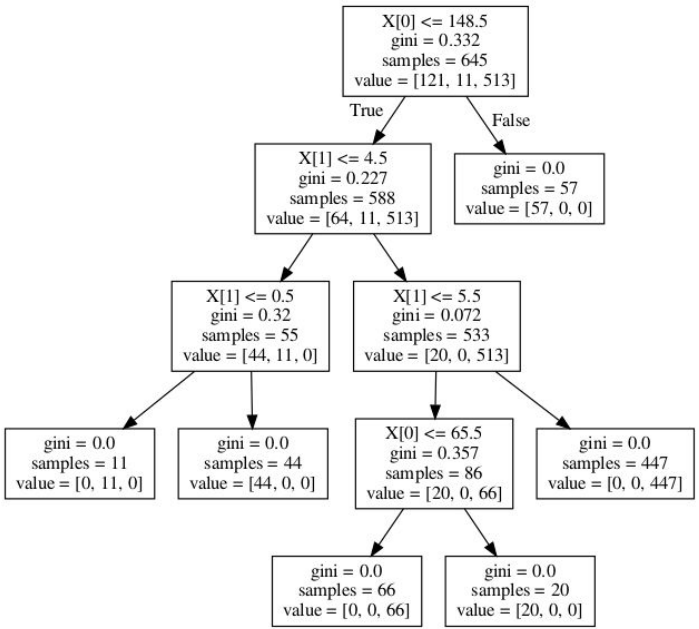
Ego

Ego is controlled by us

Front

Front is environment controlled : "given to us"

- **B** : Equations of Motion
- **E+**: When to accelerate
- **E-:** When to not accelerate



× firewire_abst_10__p
× firewire_exported_dt
× final_results.txt

```
[theory]

[Rule 1] [Pos cover = 55 Neg cover = 0]
class(A,B) :-
   variab(A,C), lteq(C,148), state(A,D), lteq(
   D,4),
   random(B,[0.775862068965517-move,0.20689655172
   4138-round,0.0172413793103448-time]).

[Rule 2] [Pos cover = 533 Neg cover = 0]
class(A,B) :-
   variab(A,C), lteq(C,148), not (state(A,D),lteq
   (D,4)), random(B,[0.958955223880597-time,0.039
   1791044776119-move,0.00186567164179104-round])
   .

[Rule 3] [Pos cover = 57 Neg cover = 0]
class(A,B) :-
   not (variab(A,C),lteq(C,148)), random(B,[0.966
   666666666667-move,0.0166666666666667-round,0.0
   166666666666667-time]).

[Training set performance]
           Actual
        +          -
     + 645         0         645
Pred
     -  0          0          0

        645        0         645

Accuracy = 1.0
[Training set summary] [[645,0,0,0]]
```

WHY?

For Starters: *ILP*

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Towards a succinct representation ?
You decide the vocabulary!

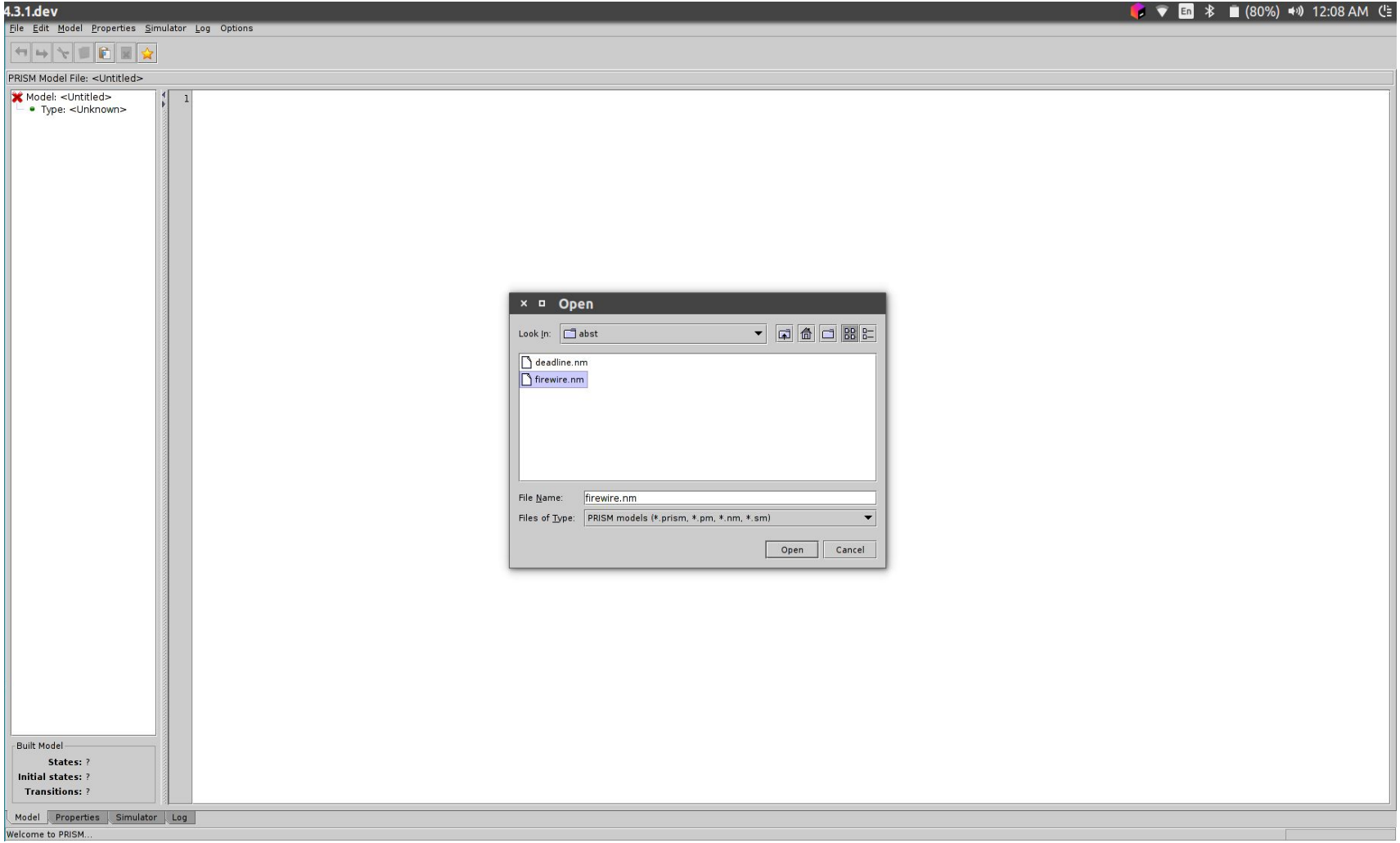
Dataset	Decision Tree Leaves	ILP Rules	Accuracy on Training Set
Cruise [a]	68	130	100%
Firewire	14	3	100%

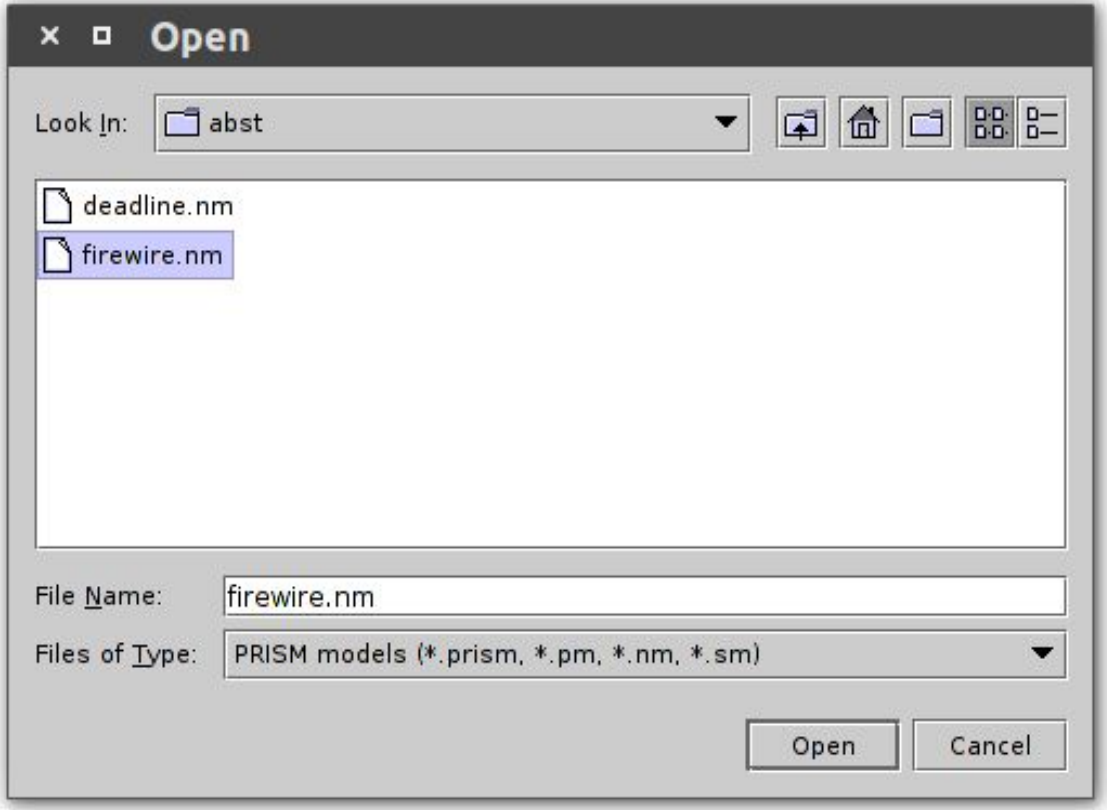
[a] A smaller sample of 5000 points.

Dataset	Decision Tree Leaves	ILP Rules	Accuracy on Training Set
Cruise [a]	68	130	100%
Firewire	14	3	100%

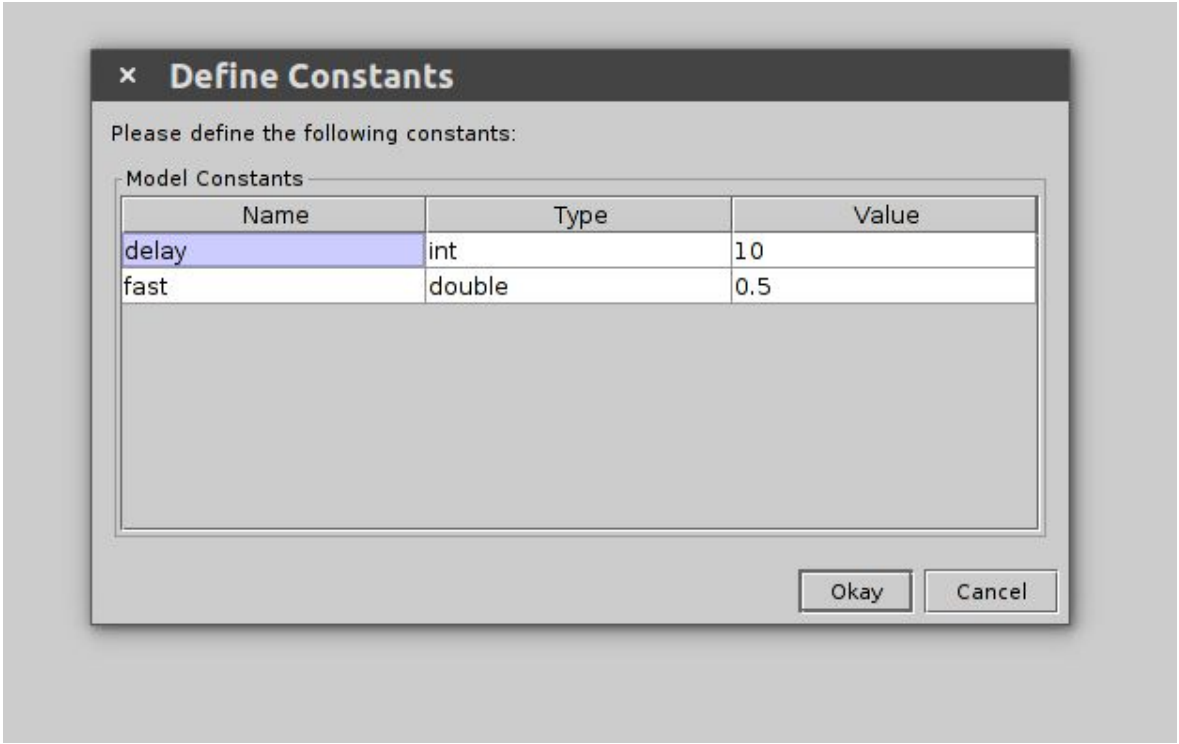
[a] A smaller sample of 5000 points.

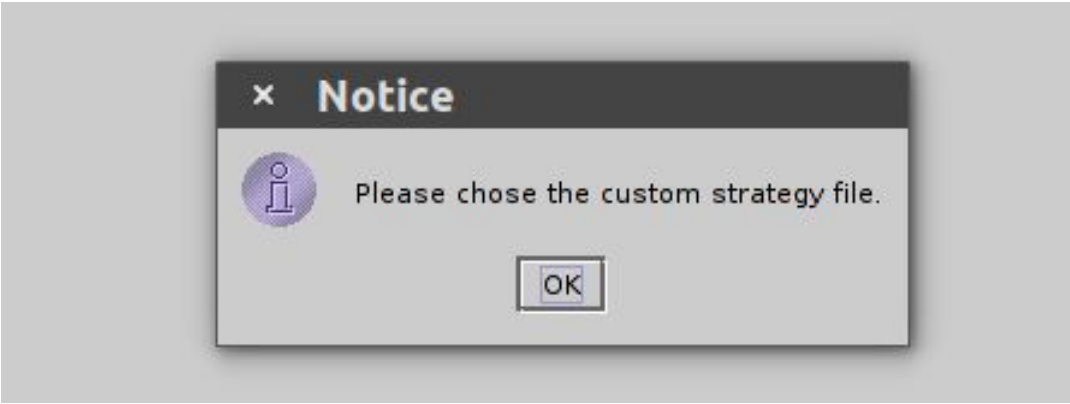
Simulating Custom Decision Tree Strategy in PRISM


4.3.1.dev
(80%) 12:08 AM
File Edit Model Properties Simulator Log Options
PRISM Model File: <Untitled>
Model: <Untitled>
Type: <Unknown>
1
Open
Look In:
abst
deadline.nm
firewire.nm
File Name:
firewire.nm
Files of Type:
PRISM models (*.prism, *.pm, *.nm, *.sm)
Open
Cancel
Built Model
States: ?
Initial states: ?
Transitions: ?
Model
Properties
Simulator
Log
Welcome to PRISM...


Open
Look In:
abst
deadline.nm
firewire.nm
File Name:
firewire.nm
Files of Type:
PRISM models (*.prism, *.pm, *.nm, *.sm)
Open
Cancel

```
// integer semantics version of abstract firewire protocol
// gxn 23/05/2001

mdp

// wire delay
const int delay;

// probability of choosing fast and slow
const double fast;
const double slow = 1-fast;

// largest constant the clock of the system is compared to
const int kx = 167;

module abstract_firewire

	// clock
	x : [0..kx+1];

	// local state
	s : [0..9];
	// 0 -start_start
	// 1 -fast_start
	// 2 -start_fast
	// 3 -start_slow
	// 4 -slow_start
	// 5 -fast_fast
	// 6 -fast_slow
	// 7 -slow_fast
	// 8 -slow_slow
	// 9 -done

	// initial state
	[time] s=0 & x<delay -> (x'=min(x+1,kx+1));
	[round] s=0 -> fast : (s'=1) + slow : (s'=4);
	[round] s=0 -> fast : (s'=2) + slow : (s'=3);
	// fast_start
	[time] s=1 & x<delay -> (x'=min(x+1,kx+1));
	[] s=1 -> fast : (s'=5) & (x'=0) + slow : (s'=6) & (x'=0);
	// start_fast
	[time] s=2 & x<delay -> (x'=min(x+1,kx+1));
	[] s=2 -> fast : (s'=5) & (x'=0) + slow : (s'=7) & (x'=0);
	// start_slow
	[time] s=3 & x<delay -> (x'=min(x+1,kx+1));
	[] s=3 -> fast : (s'=6) & (x'=0) + slow : (s'=8) & (x'=0);
	// slow_start
	[time] s=4 & x<delay -> (x'=min(x+1,kx+1));
	[] s=4 -> fast : (s'=7) & (x'=0) + slow : (s'=8) & (x'=0);
	// fast_fast
	[time] s=5 & (x<85) -> (x'=min(x+1,kx+1));
	[] s=5 & (x>=76) -> (s'=0) & (x'=0);
	[] s=5 & (x>=76-delay) -> (s'=9) & (x'=0);
	// fast_slow
	[time] s=6 & x<167 -> (x'=min(x+1,kx+1));
	[] s=6 & x>=159-delay -> (s'=9) & (x'=0);
	// slow_fast
	[time] s=7 & x<167 -> (x'=min(x+1,kx+1));
	[] s=7 & x>=159-delay -> (s'=9) & (x'=0);
	// slow_slow
```


Define Constants
Please define the following constants:
Model Constants
Name
Type
Value
delay
int
10
fast
double
0.5
Okay
Cancel


Notice
Please chose the custom strategy file.
OK

```
num_nodes=11
num_classes=3
depth=4
node lc rc predicate/action
0 1 10 X0<=148.5
1 2 5 X1<=4.5
2 3 4 X1<=0.5
3 -1 -1 round
4 -1 -1 move
5 6 9 X1<=5.5
6 7 8 X0<=65.5
7 -1 -1 time
8 -1 -1 move
9 -1 -1 time
10 -1 -1 move
num_features=2
X0:x
X1:s
```

3.1.dev

File Edit Model Properties Simulator Log Options

Automatic exploration

Custom Strategy S... | Simulate

Steps | 1

Backtracking

Backtrack

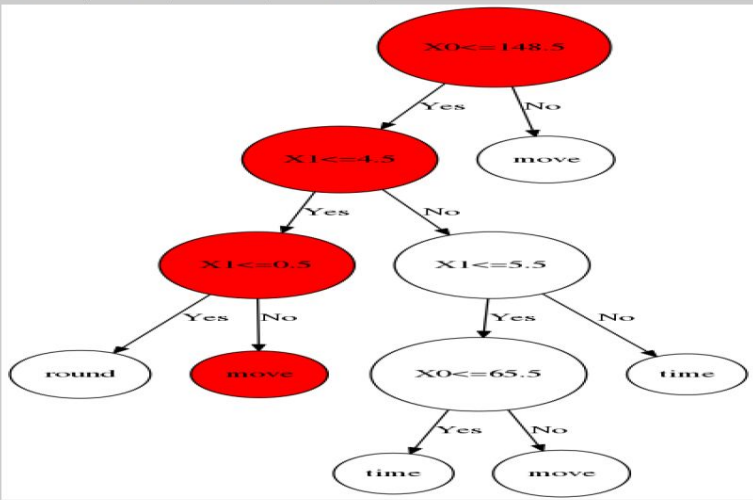
Steps | 1

Manual exploration

Module/[action]	Probability	Update
[time]	1.0	x'=1

Generate time automatically

Decision tree | State labels | Path formulae | Path information

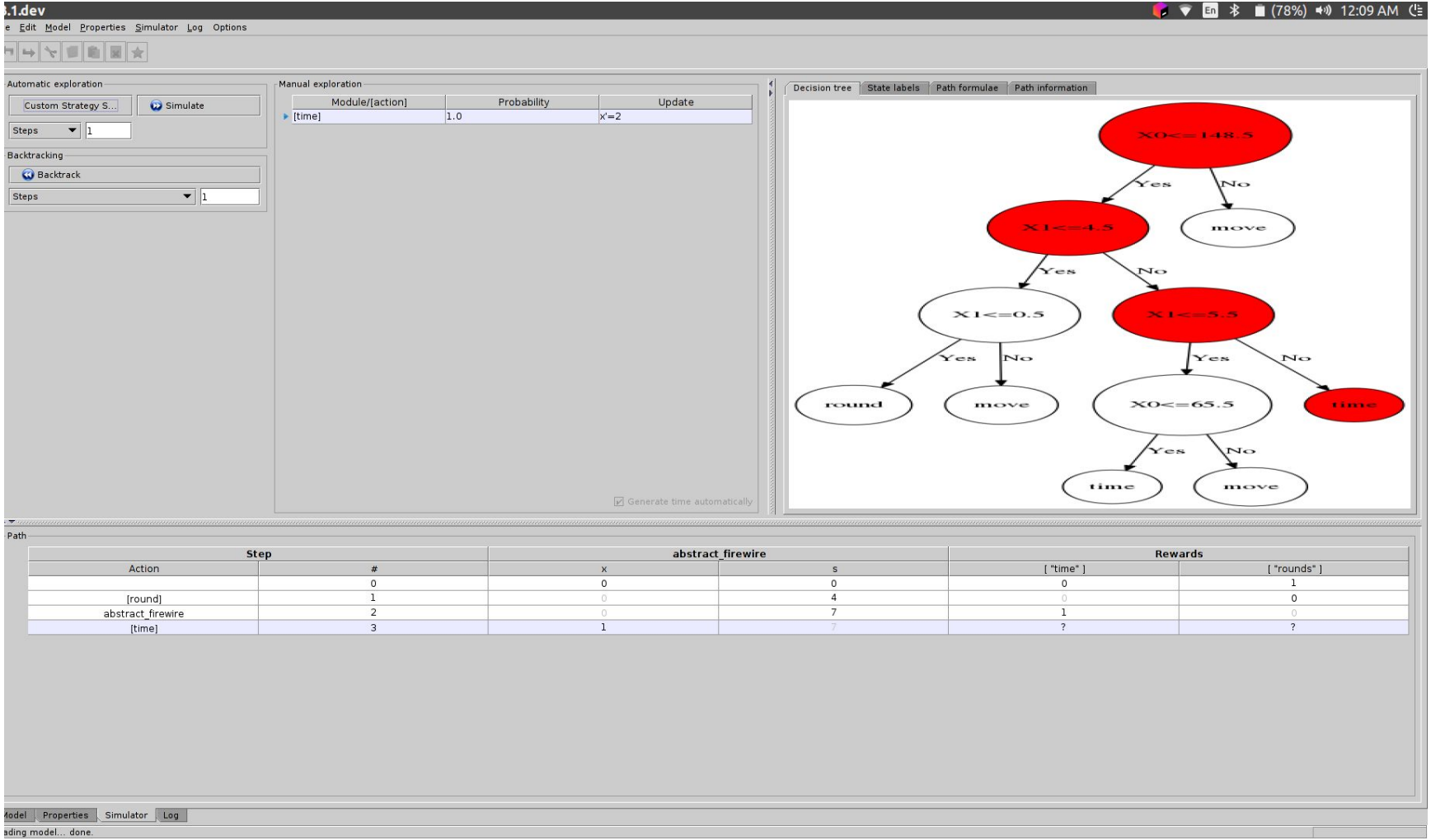


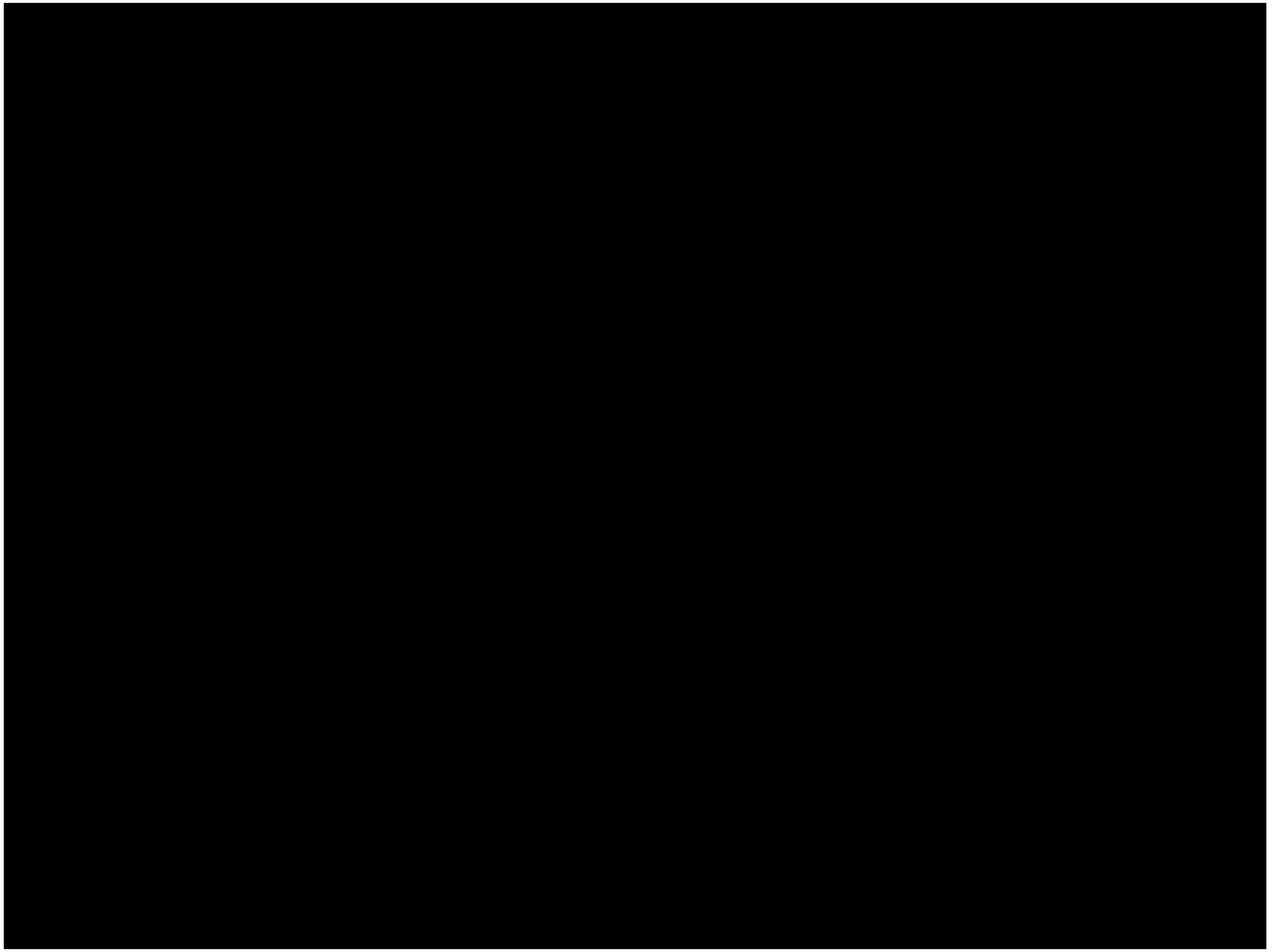
Path

Step		abstract_firewire		Rewards	
Action	#	x	s	["time"]	["rounds"]
	0	0	0	0	1
[round]	1	0	4	0	0
abstract_firewire	2	0	7	?	?

Model | Properties | Simulator | Log

oading model... done.


.1.dev
Edit Model Properties Simulator Log Options
Automatic exploration
Custom Strategy S...
Simulate
Steps
1
Backtracking
Backtrack
Steps
1
Manual exploration
Module/[action]
Probability
Update
[time]
1.0
x'=2
Generate time automatically
Decision tree
State labels
Path formulae
Path information
X0<=148.5
Yes
No
move
X1<=4.5
Yes
No
X1<=0.5
X1<=5.5
Yes
No
Yes
No
round
move
X0<=65.5
time
Yes
No
time
move
Path
Step
abstract_firewire
Rewards
Action
#
x
s
["time"]
["rounds"]
0
0
0
1
[round]
1
0
4
0
0
abstract_firewire
2
0
7
1
0
[time]
3
1
7
?
?
Model
Properties
Simulator
Log
ading model... done.



Real Life System
+ Specifications

Safety is critical

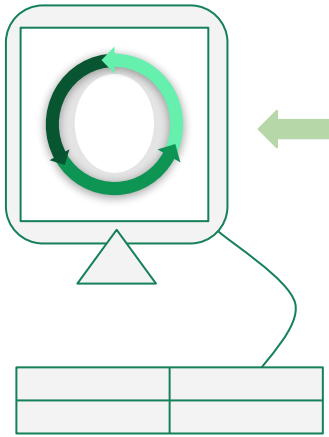
Testing, Validation..

Model Checker
(Model + Properties)

Controller Strategy

??

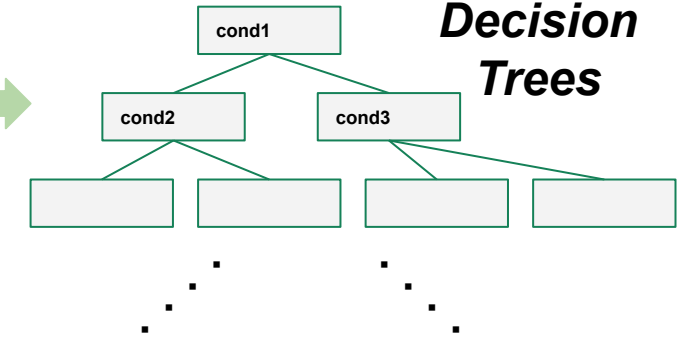
Simulating the system and visualising the strategy simultaneously



ILP

Domain Knowledge Included

Rules
When this, do this….
(readable)



Decision Trees

Machine Learning

THANK YOU