Online appendix for the paper

## Bridging Commonsense Reasoning and Probabilistic Planning via a Probabilistic Action Language

published in Theory and Practice of Logic Programming

Yi Wang*, Shiqi Zhang\#, Joohyung Lee*
*Arizona State University, USA \# SUNY Binghamton, USA

## Appendix A Extended Review of Preliminaries

## A. 1 Review: Language $\mathrm{LP}^{\mathrm{MLN}}$

An LP ${ }^{\text {MLN }}$ program is a finite set of weighted rules $w: R$ where $R$ is a rule and $w$ is a real number (in which case, the weighted rule is called soft) or $\alpha$ for denoting the infinite weight (in which case, the weighted rule is called hard). Throughout the paper, we assume that the language is propositional. Schematic variables can be introduced via grounding as usual in answer set programming.

For any $\mathrm{LP}^{\mathrm{MLN}}$ program $\Pi$ and any interpretation $I, \bar{\Pi}$ denotes the usual (unweighted) ASP program obtained from $\Pi$ by dropping the weights, and $\Pi_{I}$ denotes the set of $w: R$ in $\Pi$ such that $I \models R$.

In general, an $L P^{M L N}$ program may even have stable models that violate some hard rules, which encode definite knowledge. However, throughout the paper, we restrict attention to $\mathrm{LP}^{\mathrm{MLN}}$ programs whose stable models do not violate hard rules. More precisely, given a ground LP ${ }^{\text {MLN }}$ program $\Pi, \operatorname{SM}[\Pi]$ denotes the set

$$
\left\{I \mid I \text { is a (deterministic) stable model of } \Pi_{I} \text { that satisfies all hard rules in } \Pi\right\} .
$$

The weight of an interpretation $I$, denoted $W_{\Pi}(I)$, is defined as

$$
W_{\Pi}(I)= \begin{cases}\exp \left(\sum_{w: R \in \Pi_{I}} w\right) & \text { if } I \in \mathrm{SM}[\Pi] \\ 0 & \text { otherwise }\end{cases}
$$

and the probability of $I$, denoted $P_{\Pi}(I)$, is defined as

$$
P_{\Pi}(I)=\frac{W_{\Pi}(I)}{\sum_{J \in \mathrm{SM}[\Pi]} W_{\Pi}(J)}
$$

## A. 2 Review: DT-LP ${ }^{\text {MLN }}$

We extend the syntax and the semantics of LP ${ }^{M L N}$ to DT-LP ${ }^{M L N}$ by introducing atoms of the form

$$
\begin{equation*}
\text { utility }(u, \mathbf{t}) \tag{A1}
\end{equation*}
$$

where $u$ is a real number, and $\mathbf{t}$ is an arbitrary list of terms. These atoms can only occur in the head of hard rules of the form

$$
\begin{equation*}
\alpha: \text { utility }(u, \mathbf{t}) \leftarrow \operatorname{Body} \tag{A2}
\end{equation*}
$$

where Body is a list of literals. We call these rules utility rules.
The weight and the probability of an interpretation are defined the same as in $\mathrm{LP}^{\mathrm{MLN}}$. The utility of an interpretation $I$ under $\Pi$ is defined as

$$
U_{\Pi}(I)=\sum_{\operatorname{utility}(u, \mathbf{t}) \in I} u
$$

The expected utility of a proposition $A$ is defined as

$$
\begin{equation*}
E\left[U_{\Pi}(A)\right]=\sum_{I \models A} U_{\Pi}(I) \times P_{\Pi}(I \mid A) \tag{A3}
\end{equation*}
$$

## A. 3 Review: Multi-Valued Probabilistic Programs

Multi-valued probabilistic programs (Lee and Wang 2016) are a simple fragment of $\mathrm{LP}^{\mathrm{MLN}}$ that allows us to represent probability more naturally.

We assume that the propositional signature $\sigma$ is constructed from "constants" and their "values." A constant $c$ is a symbol that is associated with a finite set $\operatorname{Dom}(c)$, called the domain. The signature $\sigma$ is constructed from a finite set of constants, consisting of atoms $c=v^{7}$ for every constant $c$ and every element $v$ in $\operatorname{Dom}(c)$. If the domain of $c$ is \{FALSE, TRUE\} then we say that $c$ is Boolean, and abbreviate $c=$ TRUE as $c$ and $c=$ FALSE as $\sim c$.

We assume that constants are divided into probabilistic constants and non-probabilistic constants. A multi-valued probabilistic program $\Pi$ is a tuple $\langle P F, \Pi\rangle$, where

- PF contains probabilistic constant declarations of the following form:

$$
\begin{equation*}
p_{1}:: c=v_{1}|\cdots| p_{n}:: c=v_{n} \tag{A4}
\end{equation*}
$$

one for each probabilistic constant $c$, where $\left\{v_{1}, \ldots, v_{n}\right\}=\operatorname{Dom}(c), v_{i} \neq v_{j}, 0 \leq$ $p_{1}, \ldots, p_{n} \leq 1$ and $\sum_{i=1}^{n} p_{i}=1$. We use $M_{\Pi}\left(c=v_{i}\right)$ to denote $p_{i}$. In other words, $P F$ describes the probability distribution over each "random variable" $c$.

- $\Pi$ is a set of rules such that the head contains no probabilistic constants.

The semantics of such a program $\boldsymbol{\Pi}$ is defined as a shorthand for $\mathrm{LP}^{\mathrm{MLN}}$ program $T(\boldsymbol{\Pi})$ of the same signature as follows.

- For each probabilistic constant declaration (A4), $T(\boldsymbol{\Pi})$ contains, for each $i=1, \ldots, n$, (i) $\ln \left(p_{i}\right): c=v_{i}$ if $0<p_{i}<1$; (ii) $\alpha: c=v_{i}$ if $p_{i}=1$; (iii) $\alpha: \perp \leftarrow c=v_{i}$ if $p_{i}=0$.
- For each rule Head $\leftarrow$ Body in $\Pi, T(\boldsymbol{\Pi})$ contains $\alpha:$ Head $\leftarrow$ Body.
- For each constant $c, T(\boldsymbol{\Pi})$ contains the uniqueness of value constraints

$$
\begin{equation*}
\alpha: \quad \perp \leftarrow c=v_{1} \wedge c=v_{2} \tag{A5}
\end{equation*}
$$

for all $v_{1}, v_{2} \in \operatorname{Dom}(c)$ such that $v_{1} \neq v_{2}$, and the existence of value constraint

$$
\begin{equation*}
\alpha: \quad \perp \leftarrow \neg \bigvee_{v \in \operatorname{Dom}(c)} c=v . \tag{A6}
\end{equation*}
$$

In the presence of the constraints (A5) and (A6), assuming $T(\boldsymbol{\Pi})$ has at least one (probabilistic) stable model that satisfies all the hard rules, a (probabilistic) stable model $I$ satisfies $c=v$ for exactly one value $v$, so we may identify $I$ with the value assignment that assigns $v$ to $c$.

[^0]
## A. 4 Review: Action Language $p \mathcal{B C}+$ with Utility

$$
\text { Syntax of } p \mathcal{B C}+
$$

We assume a propositional signature $\sigma$ as defined in Section A.3. We further assume that the signature of an action description is divided into four groups: fluent constants, action constants, pf (probability fact) constants and initpf (initial probability fact) constants. Fluent constants are further divided into regular and statically determined. The domain of every action constant is Boolean. A fluent formula is a formula such that all constants occurring in it are fluent constants.

The following definition of $p \mathcal{B C}+$ is based on the definition of $\mathcal{B C}+$ language from (Babb and Lee 2015).

A static law is an expression of the form

$$
\begin{equation*}
\text { caused } F \text { if } G \tag{A7}
\end{equation*}
$$

where $F$ and $G$ are fluent formulas.
A fluent dynamic law is an expression of the form

$$
\begin{equation*}
\text { caused } F \text { if } G \text { after } H \tag{A8}
\end{equation*}
$$

where $F$ and $G$ are fluent formulas and $H$ is a formula, provided that $F$ does not contain statically determined constants and $H$ does not contain initpf constants.

A pf constant declaration is an expression of the form

$$
\begin{equation*}
\text { caused } c=\left\{v_{1}: p_{1}, \ldots, v_{n}: p_{n}\right\} \tag{A9}
\end{equation*}
$$

where $c$ is a pf constant with domain $\left\{v_{1}, \ldots, v_{n}\right\}, 0<p_{i}<1$ for each $i \in\{1, \ldots, n\}^{8}$, and $p_{1}+\cdots+p_{n}=1$. In other words, (A9) describes the probability distribution of $c$.

An initpf constant declaration is an expression of the form (A9) where $c$ is an initpf constant. An initial static law is an expression of the form

$$
\begin{equation*}
\text { initially } F \text { if } G \tag{A10}
\end{equation*}
$$

where $F$ is a fluent constant and $G$ is a formula that contains neither action constants nor pf constants.
A causal law is a static law, a fluent dynamic law, a pf constant declaration, an initpf constant declaration, or an initial static law. An action description is a finite set of causal laws.

We use $\sigma^{f l}$ to denote the set of fluent constants, $\sigma^{a c t}$ to denote the set of action constants, $\sigma^{p f}$ to denote the set of pf constants, and $\sigma^{\text {initpf }}$ to denote the set of initpf constants. For any signature $\sigma^{\prime}$ and any $i \in\{0, \ldots, m\}$, we use $i: \sigma^{\prime}$ to denote the set $\left\{i: a \mid a \in \sigma^{\prime}\right\}$.

By $i: F$ we denote the result of inserting $i$ : in front of every occurrence of every constant in formula $F$. This notation is straightforwardly extended when $F$ is a set of formulas.

## Semantics of $p \mathcal{B C}+$

Given a non-negative integer $m$ denoting the maximum length of histories, the semantics of an action description $D$ in $p \mathcal{B C}+$ is defined by a reduction to multi-valued probabilistic program $\operatorname{Tr}(D, m)$, which is the union of two subprograms $D_{m}$ and $D_{i n i t}$ as defined below.

[^1]For an action description $D$ of a signature $\sigma$, we define a sequence of multi-valued probabilistic program $D_{0}, D_{1}, \ldots$, so that the stable models of $D_{m}$ can be identified with the paths in the transition system described by $D$.

The signature $\sigma_{m}$ of $D_{m}$ consists of atoms of the form $i: c=v$ such that

- for each fluent constant $c$ of $D, i \in\{0, \ldots, m\}$ and $v \in \operatorname{Dom}(c)$,
- for each action constant or pf constant $c$ of $D, i \in\{0, \ldots, m-1\}$ and $v \in \operatorname{Dom}(c)$.

For $x \in\{a c t, f l, p f\}$, we use $\sigma_{m}^{x}$ to denote the subset of $\sigma_{m}$

$$
\left\{i: c=v \mid i: c=v \in \sigma_{m} \text { and } c \in \sigma^{x}\right\} .
$$

For $i \in\{0, \ldots, m\}$, we use $i: \sigma^{x}$ to denote the subset of $\sigma_{m}^{x}$

$$
\left\{i: c=v \mid i: c=v \in \sigma_{m}^{x}\right\} .
$$

We define $D_{m}$ to be the multi-valued probabilistic program $\langle P F, \Pi\rangle$, where $\Pi$ is the conjunction of

$$
\begin{equation*}
i: F \leftarrow i: G \tag{A11}
\end{equation*}
$$

for every static law (A7) in $D$ and every $i \in\{0, \ldots, m\}$,

$$
\begin{equation*}
i+1: F \leftarrow(i+1: G) \wedge(i: H) \tag{A12}
\end{equation*}
$$

for every fluent dynamic law (A8) in $D$ and every $i \in\{0, \ldots, m-1\}$,

$$
\begin{equation*}
\{0: c=v\}^{\mathrm{ch}} \tag{A13}
\end{equation*}
$$

for every regular fluent constant $c$ and every $v \in \operatorname{Dom}(c)$,

$$
\begin{equation*}
\{i: c=\text { TRUE }\}^{\mathrm{ch}}, \quad\{i: c=\text { FALSE }\}^{\mathrm{ch}} \tag{A14}
\end{equation*}
$$

for every action constant $c$, and $P F$ consists of

$$
\begin{equation*}
p_{1}:: i: p f=v_{1}|\cdots| p_{n}:: i: p f=v_{n} \tag{A15}
\end{equation*}
$$

( $i=0, \ldots, m-1$ ) for each pf constant declaration (A9) in $D$ that describes the probability distribution of $p f$.

In addition, we define the program $D_{\text {init }}$, whose signature is $0: \sigma^{\text {initp } f} \cup 0: \sigma^{f l} . D_{\text {init }}$ is the multi-valued probabilistic program

$$
D_{i n i t}=\left\langle P F^{i n i t}, \Pi^{i n i t}\right\rangle
$$

where $\Pi^{\text {init }}$ consists of the rule

$$
\perp \leftarrow \neg(0: F) \wedge 0: G
$$

for each initial static law (A10), and $P F^{\text {init }}$ consists of

$$
p_{1}:: 0: p f=v_{1} \quad|\ldots| \quad p_{n}:: 0: p f=v_{n}
$$

for each initpf constant declaration (A9).
We define $\operatorname{Tr}(D, m)$ to be the union of the two multi-valued probabilistic program $\left\langle P F \cup P F^{i n i t}, \Pi \cup \Pi^{i n i t}\right\rangle$.

For any $\mathrm{LP}^{\mathrm{MLN}}$ program $\Pi$ of signature $\sigma$ and a value assignment $I$ to a subset $\sigma^{\prime}$ of $\sigma$, we say $I$ is a residual (probabilistic) stable model of $\Pi$ if there exists a value assignment $J$ to $\sigma \backslash \sigma^{\prime}$ such that $I \cup J$ is a (probabilistic) stable model of $\Pi$.

For any value assignment $I$ to constants in $\sigma$, by $i: I$ we denote the value assignment to constants in $i: \sigma$ so that $i: I \models(i: c)=v$ iff $I \models c=v$.

We define a state as an interpretation $I^{f l}$ of $\sigma^{f l}$ such that $0: I^{f l}$ is a residual (probabilistic) stable model of $D_{0}$. A transition of $D$ is a triple $\left\langle s, e, s^{\prime}\right\rangle$ where $s$ and $s^{\prime}$ are interpretations of $\sigma^{f l}$ and $e$ is a an interpretation of $\sigma^{a c t}$ such that $0: s \cup 0: e \cup 1: s^{\prime}$ is a residual stable model of $D_{1}$. A pf-transition of $D$ is a pair $\left(\left\langle s, e, s^{\prime}\right\rangle, p f\right)$, where $p f$ is a value assignment to $\sigma^{p f}$ such that $0: s \cup 0: e \cup 1: s^{\prime} \cup 0: p f$ is a stable model of $D_{1}$.

A probabilistic transition system $T(D)$ represented by a probabilistic action description $D$ is a labeled directed graph such that the vertices are the states of $D$, and the edges are obtained from the transitions of $D$ : for every transition $\left\langle s, e, s^{\prime}\right\rangle$ of $D$, an edge labeled $e: p$ goes from $s$ to $s^{\prime}$, where $p=\operatorname{Pr}_{D_{1}}\left(1: s^{\prime} \mid 0: s, 0: e\right)$. The number $p$ is called the transition probability of $\left\langle s, e, s^{\prime}\right\rangle$

The soundness of the definition of a probabilistic transition system relies on the following proposition.

## Proposition 1

For any transition $\left\langle s, e, s^{\prime}\right\rangle, s$ and $s^{\prime}$ are states.
We make the following simplifying assumptions on action descriptions:

1. No concurrent execution of actions: For all transitions $\left\langle s, e, s^{\prime}\right\rangle$, we have $e \models a=$ TRUE for at most one action constant $a$;
2. Nondeterministic transitions are determined by pf constants: For any state $s$, any value assignment $e$ of $\sigma^{a c t}$, and any value assignment $p f$ of $\sigma^{p f}$, there exists exactly one state $s^{\prime}$ such that $\left(\left\langle s, e, s^{\prime}\right\rangle, p f\right)$ is a pf-transition;
3. Nondeterminism on initial states are determined by initpf constants: For any value assignment $p f_{\text {init }}$ of $\sigma^{\text {initpf }}$, there exists exactly one value assignment $f l$ of $\sigma^{f l}$ such that $0: p f_{i n i t} \cup 0: f l$ is a stable model of $D_{\text {init }} \cup D_{0}$.

For any state $s$, any value assignment $e$ of $\sigma^{a c t}$ such that at most one action is true, and any value assignment $p f$ of $\sigma^{p f}$, we use $\phi(s, e, p f)$ to denote the state $s^{\prime}$ such that $\left(\left\langle s, a, s^{\prime}\right\rangle, p f\right)$ is a pf-transition (According to Assumption 2, such $s^{\prime}$ must be unique). For any interpretation $I, i \in\{0, \ldots, m\}$ and any subset $\sigma^{\prime}$ of $\sigma$, we use $\left.I\right|_{i: \sigma^{\prime}}$ to denote the value assignment of $I$ to atoms in $i: \sigma^{\prime}$. Given any value assignment $T C$ of $0: \sigma^{i n i t p f} \cup \sigma_{m}^{p f}$ and a value assignment $A$ of $\sigma_{m}^{a c t}$, we construct an interpretation $I_{T C \cup A}$ of $\operatorname{Tr}(D, m)$ that satisfies $T C \cup A$ as follows:

- For all atoms $p$ in $\sigma_{m}^{p f} \cup 0: \sigma^{\text {initpf }}$, we have $I_{T C \cup A}(p)=T C(p)$;
- For all atoms $p$ in $\sigma_{m}^{a c t}$, we have $I_{T C \cup A}(p)=A(p)$;
- $\left.\left(I_{T C \cup A}\right)\right|_{0: \sigma^{f l}}$ is the assignment such that $\left.\left(I_{T C \cup A}\right)\right|_{0: \sigma^{f l} \cup 0: \sigma^{\text {initpf }}}$ is a stable model of $D_{i n i t} \cup D_{0}$.
- For each $i \in\{1, \ldots, m\}$,

$$
\left.\left(I_{T C \cup A}\right)\right|_{i: \sigma^{f l}}=\phi\left(\left.\left(I_{T C \cup A}\right)\right|_{(i-1): \sigma^{f l}},\left.\left(I_{T C \cup A}\right)\right|_{(i-1): \sigma^{a c t}},\left.\left(I_{T C \cup A}\right)\right|_{(i-1): \sigma^{p f}}\right)
$$

By Assumptions 2 and 3, the above construction produces a unique interpretation.
It can be seen that in the multi-valued probabilistic program $\operatorname{Tr}(D, m)$ translated from $D$, the probabilistic constants are $0: \sigma^{\text {initpf }} \cup \sigma_{m}^{p f}$. We thus call the value assignment of an interpretation $I$ on $0: \sigma^{\text {initpf }} \cup \sigma_{m}^{p f}$ the total choice of $I$. The following theorem asserts that the probability of a stable model under $\operatorname{Tr}(D, m)$ can be computed by simply dividing the probability of the total choice associated with the stable model by the number of choice of actions.

Theorem 1
For any value assignment $T C$ of $0: \sigma^{\text {initp } f} \cup \sigma_{m}^{p f}$ and any value assignment $A$ of $\sigma_{m}^{a c t}$, there exists exactly one stable model $I_{T C \cup A}$ of $\operatorname{Tr}(D, m)$ that satisfies $T C \cup A$, and the probability of $I_{T C \cup A}$ is

$$
\operatorname{Pr}_{T r(D, m)}\left(I_{T C \cup A}\right)=\frac{\prod_{c=v \in T C} M(c=v)}{\left(\left|\sigma^{a c t}\right|+1\right)^{m}}
$$

The following theorem tells us that the conditional probability of transiting from a state $s$ to another state $s^{\prime}$ with action $e$ remains the same for all timesteps, i.e., the conditional probability of $i+1: s^{\prime}$ given $i: s$ and $i: e$ correctly represents the transition probability from $s$ to $s^{\prime}$ via $e$ in the transition system.

## Theorem 2

For any state $s$ and $s^{\prime}$, and action $e$, we have

$$
\operatorname{Pr}_{\operatorname{Tr}(D, m)}\left(i+1: s^{\prime} \mid i: s, i: e\right)=\operatorname{Pr}_{T r(D, m)}\left(j+1: s^{\prime} \mid j: s, j: e\right)
$$

for any $i, j \in\{0, \ldots, m-1\}$ such that $\operatorname{Pr}_{\operatorname{Tr}(D, m)}(i: s)>0$ and $\operatorname{Pr}_{\operatorname{Tr}(D, m)}(j: s)>0$.
For every subset $X_{m}$ of $\sigma_{m} \backslash \sigma_{m}^{p f}$, let $X^{i}(i<m)$ be the triple consisting of

- the set consisting of atoms $A$ such that $i: A$ belongs to $X_{m}$ and $A \in \sigma^{f l}$;
- the set consisting of atoms $A$ such that $i: A$ belongs to $X_{m}$ and $A \in \sigma^{a c t}$;
- the set consisting of atoms $A$ such that $i+1: A$ belongs to $X_{m}$ and $A \in \sigma^{f l}$.

Let $p\left(X^{i}\right)$ be the transition probability of $X^{i}, s_{0}$ is the interpretation of $\sigma_{0}^{f l}$ defined by $X^{0}$, and $e_{i}$ be the interpretations of $i: \sigma^{a c t}$ defined by $X^{i}$.

Since the transition probability remains the same, the probability of a path given a sequence of actions can be computed from the probabilities of transitions.

## Corollary 1

For every $m \geq 1, X_{m}$ is a residual (probabilistic) stable model of $\operatorname{Tr}(D, m)$ iff $X^{0}, \ldots, X^{m-1}$ are transitions of $D$ and $0: s_{0}$ is a residual stable model of $D_{\text {init }}$. Furthermore,

$$
\begin{gathered}
\operatorname{Pr}_{T r(D, m)}\left(X_{m} \mid 0: e_{0}, \ldots, m-1: e_{m-1}\right)=p\left(X^{0}\right) \times \cdots \times p\left(X^{m}\right) \times \operatorname{Pr}_{T r(D, m)}\left(0: s_{0}\right) \\
p \mathcal{B C}+\text { with Utility }
\end{gathered}
$$

Wang and Lee (2019) has extended $p \mathcal{B C}+$ with the notion of utility as follows.
We extend $p \mathcal{B C}+$ by introducing the following expression called utility law that assigns a reward to transitions:

$$
\begin{equation*}
\text { reward } v \text { if } F \text { after } G \tag{A16}
\end{equation*}
$$

where $v$ is a real number representing the reward, $F$ is a formula that contains fluent constants only, and $G$ is a formula that contains fluent constants and action constants only (no pf, no initpf constants). We extend the signature of $\operatorname{Tr}(D, m)$ with a set of atoms of the form (A1). We turn a utility law of the form (A16) into the $\mathrm{LP}^{\mathrm{MLN}}$ rule

$$
\begin{equation*}
\alpha: \operatorname{utility}(v, i+1, i d) \leftarrow(i+1: F) \wedge(i: G) \tag{A17}
\end{equation*}
$$

where $i d$ is a unique number assigned to the $\operatorname{LP}^{\mathrm{MLN}}$ rule and $i \in\{0, \ldots, m-1\}$.
Given a nonnegative integer $m$ denoting the maximum timestamp, a $p \mathcal{B C}+$ action description
$D$ with utility over multi-valued propositional signature $\sigma$ is defined as a high-level representation of the DT-LP ${ }^{\text {MLN }}$ program $\left(\operatorname{Tr}(D, m), \sigma_{m}^{a c t}\right)$.

We extend the definition of a probabilistic transition system as follows: A probabilistic transition system $T(D)$ represented by a probabilistic action description $D$ is a labeled directed graph such that the vertices are the states of $D$, and the edges are obtained from the transitions of $D$ : for every transition $\left\langle s, e, s^{\prime}\right\rangle$ of $D$, an edge labeled $e: p, u$ goes from $s$ to $s^{\prime}$, where $p=\operatorname{Pr}_{D_{1}}\left(1: s^{\prime} \mid 0: s \wedge 0: e\right)$ and $u=E\left[U_{D_{1}}\left(0: s \wedge 0: e \wedge 1: s^{\prime}\right)\right]$. The number $p$ is called the transition probability of $\left\langle s, e, s^{\prime}\right\rangle$, denoted by $p\left(s, e, s^{\prime}\right)$, and the number $u$ is called the transition reward of $\left\langle s, e, s^{\prime}\right\rangle$, denoted by $u\left(s, e, s^{\prime}\right)$.

## Appendix B PBCPLUS2POMDP in Compositional Way

In particular, the inputs of PBCPLUS2POMDP(COMPO) include the following:

- LP ${ }^{\text {MLN }}$ program $\Pi(m)$, parameterized with maximum timestep $m$, that contains LP $^{\text {MLN }}$ translation of fluent dynamic laws, observation dynamic laws and utility laws with no occurrence of action constant, and static laws, as well as pf constant declarations of pf constants that occur in those causal laws (see Figure 1);
- For each group of actions $a_{i} \in \operatorname{in} a_{1}, \ldots, a_{n}$, an $\mathrm{LP}^{\mathrm{MLN}}$ program $\Pi_{i}(m) \cup C_{i}(m)$, parameterized with maximum timestep $m ; \Pi_{i}(m)$ contains translation of fluent dynamic laws, observation dynamic laws and utility laws where only actions in $a_{i}$ can occur in the body, as well as pf constant declarations of pf constants that occurs in those causal laws; $C_{i}(m)$ contains choice rules (possibly with cardinality bounds) to generate exactly one action in the group $a_{i}$; It is up to the user how to group the actions;
- Discount factor.

The system outputs the POMDP definition $M(D)$, so that $D_{m}=\Pi(m) \cup \Pi_{1}(m) \cup \ldots \Pi_{n}(m) \cup$ $C(m)$, where $C(m)$ is the choice rule with cardinality constraint to generate at most one action in $a_{1}, \ldots, a_{n}$ for each timestep $i \in\{0, \ldots, m-1\}$. The transition probabilities, observation probabilities and reward function of $M(D)$ are obtained by conjoining those from each of $\Pi \cup$ $\Pi_{i} \cup C_{i}(i \in\{1, \ldots, n\})$.

Formally, let $\mathbf{S}, \Omega, P_{M(D)}, O_{M(D)}, R_{M(D)}$ be the set of states, the set of observations, transition probabilities, observation probabilities and reward function of $M(D)$, resp. system PBCPLUS2POMDP calls LPMLN2ASP first to solve $\Pi(0)$ to obtain $\mathbf{S}$, and then $\Pi(1) \cup \Pi_{i}(1) \cup C_{i}(1)$ to obtain $P_{M(D)}, O_{M(D)}, R_{M(D)}$ as follows:

$$
\begin{gathered}
P_{M(D)}\left(s, a, s^{\prime}\right)=P_{\Pi(1) \cup \Pi_{i}(1) \cup C_{i}(1)}\left(1: s^{\prime} \mid 0: s, 0: a\right) \\
O_{M(D)}(s, a, o)=P_{\Pi(1) \cup \Pi_{i}(1) \cup C_{i}(1)}(1: o \mid 1: s, 0: a) \\
R_{M(D)}\left(s, a, s^{\prime}\right)=E\left[U_{\Pi(1) \cup \Pi_{i}(1) \cup C_{i}(1)}\left(0: s, 0: a, 1: s^{\prime}\right)\right]
\end{gathered}
$$

for each $a \in a_{i}, s, s^{\prime} \in \mathbf{S}$ and $o \in \Omega$.

## Example 1

For the dialog example, we group the actions as follows: $\{\operatorname{ConfirmItem}(i) \mid i \in \operatorname{Item}\},\{\operatorname{ConfirmPerson}(p) \mid$ $p \in$ Person $\}$, $\{$ ConfirmRoom $(r) \mid r \in$ Room $\},\{$ WhichItem $\},\{$ WhichPerson $\},\{$ WhichRoom $\}$, $\{$ Deliver $(i, p, r) \mid i \in$ Item, $p \in$ Person, $r \in$ Room $\}$.
$\Pi$ is

```
astep(0..m-1).
step(0..m).
boolean(t; f).
item(coffee; coke; cookies; burger).
person(alice; bob; carol).
room(r1; r2; r3).
% UEC
:- obs_Item(X1, I), obs_Item(X2, I), X1 != X2.
:- not obs_Item(coffee, I), not obs_Item(coke, I),
    not obs_Item(cookies, I), not obs_Item(burger, I),
    not obs_Item(na, I), step(I).
:- obs_Person(X1, I), obs_Person(X2, I), X1 != X2.
:- not obs_Person(alice, I), not obs_Person(bob, I),
    not obs_Person(carol, I), not obs_Person(na, I),
    step(I).
:- obs_Room(X1, I), obs_Room(X2, I), X1 != X2.
:- not obs_Room(r1, I), not obs_Room(r2, I),
    not obs_Room(r3, I), not obs_Room(na, I),
    step(I).
:- obs_Confirmed(X1, I), obs_Confirmed(X2, I), X1 != X2.
:- not obs_Confirmed(yes, I), not obs_Confirmed(no, I),
    not obs_Confirmed(na, I), step(I).
:- fl_ItemReq(X1, I), fl_ItemReq(X2, I), X1 != X2.
:- not fl_ItemReq(coffee, I), not fl_ItemReq(coke, I),
    not fl_ItemReq(cookies, I), not fl_ItemReq(burger, I),
    not fl_ItemReq(na, I), step(I).
:- fl_PersonReq(X1, I), fl_PersonReq(X2, I), X1 != X2
:- not fl_PersonReq(alice, I), not fl_PersonReq(bob, I),
    not fl_PersonReq(carol, I), not fl_PersonReq(na, I),
    step(I).
:- fl_RoomReq(X1, I), fl_RoomReq(X2, I), X1 != X2.
:- not fl_RoomReq(r1, I), not fl_RoomReq(r2, I),
    not fl_RoomReq(r3, I), not fl_RoomReq(na, I),
    step(I).
:- fl_Terminated(X1, I), fl_Terminated(X2, I), X1 != X2.
:- not fl_Terminated(t, I), not fl_Terminated(f, I), step(I).
%% No two observations can occur at the same time step
:- obs_Item(It, I), obs_Person(P, I), It != na, P != na.
:- obs_Item(It, I), obs_Room(R, I), It != na, R != na.
:- obs_Item(It, I), obs_Confirmed(C, I), It != na, C != na.
:- obs_Person(P, I), obs_Room(R, I), P != na, R != na.
:- obs_Person(P, I), obs_Confirmed(C, I), P != na, C != na.
:- obs_Room(R, I), obs_Confirmed(C, I), R != na, C != na.
% Inertial Fluents
{fl_ItemReq(It, I+1)} :- fl_ItemReq(It, I), astep(I).
{fl_PersonReq(P, I+1)} :- fl_PersonReq(P, I), astep(I).
{fl_RoomReq(R, I+1)} :- fl_RoomReq(R, I), astep(I).
{fl_Terminated(B, I+1)} :- fl_Terminated(B, I), astep(I).
```

\% Initial value of regular fluents and observation constants are exogenous

```
{fl_Terminated(B, 0) } :- boolean(B).
{fl_ItemReq(It, 0)} :- item(It).
{fl_PersonReq(P, 0)} :- person(P).
{fl_RoomReq(R, 0)} :- room(R).
{obs_Item(It, 0)} :- item(It).
{obs_Person(P, 0)} :- person(P).
{obs_Room(R, 0)} :- room(R).
{obs_Confirmed(yes, 0); obs_Confirmed(no, 0)}.
% By default, observation constant has na value
{obs_Item(na, I) } :- step(I).
{obs_Person(na, I) } :- step(I).
{obs_Room(na, I)} :- step(I).
{obs_Confirmed(na, I) } :- step(I).
```

$\Pi_{1}$ contains definition of action Ask2ConfirmItem:

```
% Action: ConfirmItem
:- c(It, X1, I), act_ConfirmItem(It, X2, I), X1 != X2.
:- not act_ConfirmItem(It, t, I), not act_ConfirmItem(It, f, I), item(It), astep(I).
:- pf_ConfirmWhenCorrect(X1, I), pf_ConfirmWhenCorrect(X2, I), X1 != X2.
:- not pf_ConfirmWhenCorrect(yes, I), not pf_ConfirmWhenCorrect(no, I), astep(I).
:- pf_ConfirmWhenIncorrect(X1, I), pf_ConfirmWhenIncorrect(X2, I), X1 != X2.
:- not pf_ConfirmWhenIncorrect(yes, I), not pf_ConfirmWhenIncorrect(no, I), astep(I).
@log(0.8) pf_ConfirmWhenCorrect(yes, I) :- astep(I).
@log(0.2) pf_ConfirmWhenCorrect(no, I) :- astep(I).
@log(0.2) pf_ConfirmWhenIncorrect(yes, I) :- astep(I).
@log(0.8) pf_ConfirmWhenIncorrect(no, I) :- astep(I).
obs_Confirmed(C, I+1) :- fl_ItemReq(It, I+1), fl_Terminated(f, I+1),
    act_ConfirmItem(It, t, I), pf_ConfirmWhenCorrect(C, I).
obs_Confirmed(C, I+1) :- fl_ItemReq(It, I+1), fl_Terminated(f, I+1),
    act_ConfirmItem(It1, t, I), It1 != It, pf_ConfirmWhenIncorrect(C, I).
{act_ConfirmItem(It, B, I) } :- item(It), boolean(B), astep(I).
:- not 1{act_ConfirmItem(It, t, I) : item(It)}1, astep(I).
```

    Similarly, \(\Pi_{2}, \Pi_{3}\) contains definition of actions ConfirmPerson and ConfirmRoom.
    \(\Pi_{4}\) contains definition of actions WhichItem \((t)\) :
    \% Action WhichItem
:- act_WhichItem(X1, I), act_WhichItem(X2, I), X1 != X2.
:- not act_WhichItem(t, I), not act_WhichItem(f, I), astep(I).
:- pf_WhichItem(It, X1, I), pf_WhichItem(It, X2, I), X1 != X2.
:- not pf_WhichItem(It, coffee, I), not pf_WhichItem(It, coke, I),
not pf_WhichItem(It, cookies, I), not pf_WhichItem(It, burger, I),
item(It), astep(I).
@log(0.7) pf_WhichItem(coffee, coffee, I) :- astep(I).
@log(0.1) pf_WhichItem(coffee, coke, I) :- astep(I).
@log(0.1) pf_WhichItem(coffee, cookies, I) :- astep(I).

```
@log(0.1) pf_WhichItem(coffee, burger, I) :- astep(I).
@log(0.1) pf_WhichItem(coke, coffee, I) :- astep(I).
@log(0.7) pf_WhichItem(coke, coke, I) :- astep(I).
@log(0.1) pf_WhichItem(coke, cookies, I) :- astep(I).
@log(0.1) pf_WhichItem(coke, burger, I) :- astep(I).
@log(0.1) pf_WhichItem(cookies, coffee, I) :- astep(I).
@log(0.1) pf_WhichItem(cookies, coke, I) :- astep(I).
@log(0.7) pf_WhichItem(cookies, cookies, I) :- astep(I).
@log(0.1) pf_WhichItem(cookies, burger, I) :- astep(I).
@log(0.1) pf_WhichItem(burger, coffee, I) :- astep(I).
@log(0.1) pf_WhichItem(burger, coke, I) :- astep(I).
@log(0.1) pf_WhichItem(burger, cookies, I) :- astep(I).
@log(0.7) pf_WhichItem(burger, burger, I) :- astep(I).
obs_Item(It1, I+1) :- fl_ItemReq(It, I+1), fl_Terminated(f, I+1),
    act_WhichItem(t, I), pf_WhichItem(It, It1, I).
%{act_WhichItem(B, I) } :- boolean(B), astep(I).
act_WhichItem(t, I) :- astep(I).
```

Similarly, $\Pi_{5}$ and $\Pi_{6}$ contain definitions of actions WhichPerson $(t)$ and WhichRoom $(t)$.
$\Pi_{7}$ contains definitions of action $\operatorname{Deliver}(i, p, r)$ :

```
% Action: Deliver
:- act_Deliver(It, P, R, X1, I), act_Deliver(It, P, R, X2, I), X1 != X2.
:- not act_Deliver(It, P, R, t, I), not act_Deliver(It, P, R, f, I), item(It), person(P), room(R), as
).
utility(1, I+1, It) :- fl_ItemReq(It, I+1), act_Deliver(It, P, R, t, I), fl_Terminated(f, I).
utility(1, I+1, P) :- fl_PersonReq(P, I+1), act_Deliver(It, P, R, t, I), fl_Terminated(f, I).
utility(1, I+1, R) :- fl_RoomReq(R, I+1), act_Deliver(It, P, R, t, I), fl_Terminated(f, I).
fl_Terminated(t, I+1) :- act_Deliver(It, P, R, t, I).
{act_Deliver(It, P, R, B, I) } :- item(It), person(P), room(R), boolean(B), astep(I).
:- not 1{act_Deliver(It, P, R, t, I) : item(It), person(P), room(R)}1, astep(I).
```

$\Pi_{8}$ contains definitions of no-action:

```
act_noact(I) :- astep(I).
```

With this way of grouping actions, system PBCPLUS2POMDP(COMPO) can generate POMDP for this example with $\sim 5$ minutes.

## Appendix C Tiger Example

## Example 2

(Two Tigers Example). Consider a variant of the well-known tiger example extended with two tigers. Each of the three doors has either a tiger or a prize behind. The agent can open either of the three doors. The agent can also listen to get a better idea of where the tiger is. Listening yields the correct information about where each of the two tigers is with probability 0.85 . This example can be represented in the extended $p \mathcal{B C}+$ as follows:

Notation: $l, l_{1}, l_{2}, l_{3}$ range over Left, Middle, Right, $y$ ranges over Tiger1, Tiger2
Observation constants:
Domains:

TigerPositionObserved (y)
Regular fluent constants:
TigerPosition (y)
Action constants:
Listen
OpenDoor (l)
Pf constants:
Pf_Listen
Pf_FailedListen (y)
\{Left, Middle, Right, NA\}
Domains:
\{Left, Middle, Right $\}$
Domains:
Boolean
Boolean
Domains:
Boolean
\{Left, Middle, Right $\}$

A reward of 10 is obtained for opening the door with no tiger behind. reward 10 if TigerPosition(Tiger1) $=l_{1} \wedge$ TigerPosition(Tiger2) $=l_{2}$ after $\operatorname{OpenDoor}\left(l_{3}\right)$

$$
\left(l_{1} \neq l_{3}, l_{2} \neq l_{3}\right)
$$

A penalty of 100 is imposed on opening a door with a tiger behind.

$$
\text { reward }-100 \text { if TigerPosition }(y)=l \text { after OpenDoor }(l) .
$$

Executing the action Listen has a small penalty of 1.

$$
\text { reward }-1 \text { if } T \text { after Listen. }
$$

Two tigers cannot be in the same position.

$$
\text { caused } \perp \text { if TigerPosition(Tiger1) }=l \wedge \text { TigerPosition }(\text { Tiger } 2)=l
$$

Successful listening reveals the positions of the two tigers.
observed TigerPositionObserved $(y)=l$ if TigerPosition $(y)=l$ after Listen $\wedge$ Pf_Listen.
Failed listening yields a random position for each tiger.
caused Pf_FailedListen $(y)=\left\{\operatorname{Left}: \frac{1}{3}\right.$, Middke $: \frac{1}{3}$, Right $\left.: \frac{1}{3}\right\}$,
observed TigerPositionObserved $(y)=l$ if $\top$ after Listen $\wedge \sim P f$ Listen $\wedge$ Pf_FailedListen $(y)=l$.
The positions of tigers observe the commonsense law of inertia.
inertial TigerPosition (y).
The action Listen has a success rate of 0.85 .
caused PfListen $=\{$ TRUE $: 0.85$, FALSE $: 0.15\}$.


[^0]:    ${ }^{7}$ Note that here " $=$ " is just a part of the symbol for propositional atoms, and is not equality in first-order logic.

[^1]:    ${ }^{8}$ We require $0<p_{i}<1$ for each $i \in\{1, \ldots, n\}$ for the sake of simplicity. On the other hand, if $p_{i}=0$ or $p_{i}=1$ for some $i$, that means either $v_{i}$ can be removed from the domain of $c$ or there is not really a need to introduce $c$ as a pf constant. So this assumption does not really sacrifice expressivity.

