Experiments on Psychology using the ILP+ASP method

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Abstract. The ILP+ASP method [8] is a new method for Experimental Psychology, based on Inductive Logic Programming (ILP) and Answer Set Programming (ASP). It is an application of [7] to represent, verify and learn psychological models, an alternative to the use of statistical methods. In this paper we introduce the ILP+ASP method and we apply it in two fields of Psychology: *Environmental Psychology* and *Human Reasoning and Decision Making*. Results show that ILP+ASP matches or outperforms other alternatives, namely linear regression and fast and frugal heuristics [4]. The developed models use rules near to natural language and allow to perform extended reasoning tasks.

1 Introduction

Experimental Psychology (ExP) has the aim of modeling the processes of human behavior and cognition using experimental methods. Psychological models are often incomplete and not formally defined; usually statistical methods, such as linear regression (LR), are used to complete and formalize them.

In [8] the ILP+ASP method for Psychology was proposed: Inductive Logic Programming (ILP) [6] is used to build a psychological model. Answer Set Programming (ASP) , a form of logic programming based in the stable model (answer set) semantics [3], is then used to solve reasoning tasks with it. The method can solve problems not considered in ExP, like learning on dynamic domains without the frame problem [5], and performing advanced reasoning tasks like explanation and planning.

In this paper, we introduce the ILP+ASP method and report experiments on Environmental Psychology (EnvP) and Human Reasoning and Decision Making (HRDM). Results are compared with the methods usually applied in these fields.

In EnvP, psychological models represent how some factors, like the ecological behavior of a person, can be explained based on other factors, like her beliefs, intentions, etc. One of the most important models in EnvP is the Theory of Planned Behavior [1].

HRDM is concerned with theoretical and empirical perspectives on human reasoning. The Theory of the Adaptive Toolbox (TAT) [4] proposes that human reasoning and decision making can be modeled as simple algorithms (fast and frugal heuristics).

The paper is organized as follows. Section 2 introduces the ILP+ASP method, comparing it with the usual ExP method. Sections 3 and 4 report experiments for the fields of EnvP and HRDM. Finally, section 5 presents conclusions and future work.

2 The Method of ILP+ASP

We introduce the ILP+ASP method, comparing it with the usual method of ExP.

Step 1. Psychological Theory. A psychological theory about human behavior is proposed. For example, we apply the Theory of Planned Behavior (TPB) to study *ecological behavior*, human behavior that is relevant for environmental issues (e.g. waste management). According to TPB (fig.1), the *intention* of a person to perform a behavior depends on her *attitudes* towards the behavior, on her perceived social pressure to perform it (*subjective norm*), and on her perceived ease of performing it (*perceived behavioral control*). The *behavior* depends on the intention and can depend on the perceived behavioral control.

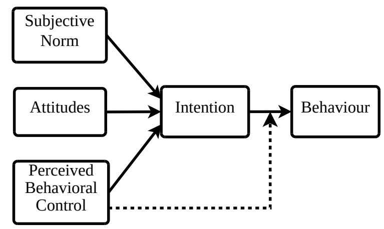

Fig. 1. Theory of Planed Behavior.

Step 2. Representation. The concepts of the theory are represented formally. In ExP, it is usual to represent them as numerical variables. For example, in TPB we could represent *behavior* as a variable from 1 to 5 (very low to very high). In the ILP+ASP method, a logic programming representation is used instead, e.g. the predicate *behavior(S,X)*, where S represents a person (*subject*) and *X* her behavior value. The form of representation is clearly improved: a logic program can represent non-linear relations, and allows the representation of simple numerical formulas as well.

Step 3. Data Collection. Experimental data is collected, usually with a survey. Each question, e.g. *Do you recycle paper and glass?*, is usually answered with a score, e.g. from 1 to 5. Answers are mapped to the concepts of the theory, e.g. the answers of all questions regarding ecological behavior can be averaged to get a single *behavior* value. Also, surveys are not a safe instrument, e.g. subjects can answer falsely or incorrectly. In ExP, it is usual to apply statistical methods to detect these cases (*outliers*). The ILP+ASP method provides 2 ways of dealing with this: ILP systems can handle noise, and ASP rules can be defined to identify these subjects.

Step 4. Model construction. A model with the particular relation among the concepts is built. In ExP, a method of LR is typically used, with the representation chosen in step 2 and the data collected in step 3. In the ILP+ASP method a logic program is built from instance data of the survey using an ILP system. ILP provides a correct and complete method for induction of logic programs; the level of correction is the same as LR.

Step 5. Reasoning. The resulting model is used to reason about human behavior. In ExP, the resulting linear equation is used for prediction. In the ILP+ASP method, this is substituted by reasoning with ASP: additional relevant tasks like explanation and planning can be performed, which are not considered in the method of ExP.

3 ILP+ASP for Environmental Psychology

We report two experiments with the ILP+ASP method on EnvP. In both cases, the psychological theory is TPB, and the same dataset is used: steps 1 and 3 of the method are the same. Experiments were performed using Progol[1]. Results are compared with LR.

A sample of 286 subjects was used[2]. The survey has 50 questions, rated with scores from 1 (very low) to 5 (very high). Several questions measure each component of TPB, e.g. 17 questions are used to measure the ecological behavior of a subject.

3.1 Experiment 1

For this experiment, we follow a usual setup in ExP: subject answers for each component of TPB are averaged to get a single value per component. The goal is to predict the *ecological behavior* (EB) of each subject, an integer value from 1 to 5 (very low to very high) based on her *intention* (INT) and *perceived behavior control* (PBC) (fig. 1).

Representation. The predicates used in this model are:

- *mean(S,C,V)*: the mean answer for subject S is V on component C (e.g. EB). $mean(S, eb, V)$ is the learning target. Values are rounded to integers.
- *gteq(X,Y)*: value X is greater or equal to value Y.

Results. The ILP+ASP model has 4 rules:

```
mean(S,eb,4) :- mean(S,int,5).
mean(S,eb,4) :- mean(S,int,4), mean(S,pbc,X), gteq(X,4).
mean(S,eb,3) :- mean(S,int,X), gteq(3,X).
mean(S,eb,3) :- mean(S,int,4), mean(S,pbc,X), gteq(3,X).
```

The linear equation found by LR is:

```
EB = 0.33*INT + 0.14*PBC + 1.59
```

Fig. 2 shows the prediction of ILP+ASP (left) and LR (right). Each cell represents a value for INT and for PBC. Circles represent the distribution of EB values from 1 (smallest) to 5 (biggest). Predicted values are marked with a black border. The darker the color of a circle, the more subjects have those INT, PBC and EB values wrt. the whole dataset. The maximum predictive accuracy will be 0.58: most subjects have high INT and PBC values (4 or 5), but in theses cases the EB can be between 3 and 5.

Both models achieve an accuracy of *0.56*, and predict similar values. This shows that ILP+ASP can match LR using the same setup and no additional background knowledge. Also, the result of ILP+ASP provides more information: while a linear equation states how much EB changes wrt. INT and PBC, rules explain how these changes happen: weak (≤ 3) or very strong (5) intentions imply a middle or strong (4) behavior. If the intention is just strong, then the PBC can rise or lower the actual behavior, as in fig 1.

The program can now be used in ASP to solve different reasoning tasks, e.g. prediction and explanation. For example, if we want to *explain* why the EB of subject $s1$ is 4 and we know that her PBC is 5, then we would add these ASP sentences:

[1] http://www.doc.ic.ac.uk/ shm/progol.html

[2] Please contact the authors for questions regarding the data.

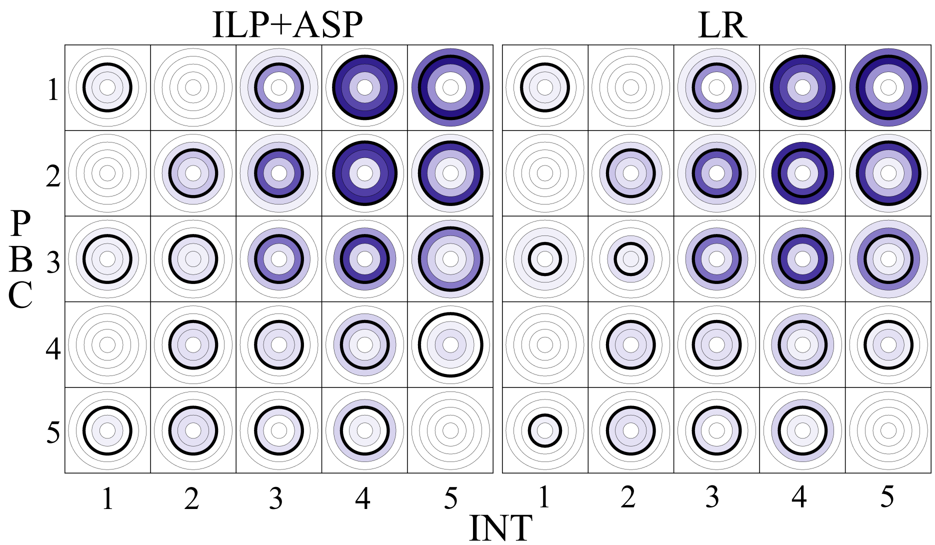

Fig. 2. Prediction of the ILP+ASP method (left) and LR (right).

```
mean(s1,pbc,5).
1{mean(s1,int,1), mean(s1,int,2), mean(s1,int,3), mean(s1,int,4),mean(s1,int,5)}1.
:- not mean(s1,eb,4).
```

The first rule states the value of PBC for $s1$, the second that one INT value must be chosen, and the third that her EB must be 4. By using an ASP system like Clasp[3] we get 2 answer sets: $\{mean(s1, int, 4)\}$, $\{mean(s1, int, 5)\}$ (intention must be 4 or 5).

3.2 Experiment 2

Next we use ILP+ASP to model the answers to questions about EB, from the answers about INT and PBC (fig. 1). Thus, the 17 specific behaviors in the survey (e.g. water consumption, waste management) will be modeled, instead of a single behavior value.

As a first approach, only subject answers are used as background knowledge: *answers(S,Q,V)* represents that S answered V to question Q. As an example, the rule:

```
answers(S,q8,3) :- answers(S,q34,3), answers(S,q47,4), answers(S,q48,4).
```

Means that a subject will show a weak behavior on waste management (question 8) if it has a weak intention (34) but a high control for this task (47,48).

Accuracy was assessed using a 10-fold cross validation. For all questions, ILP+ASP matched or outperformed LR, although it performed only slightly better than a majority class model, e.g. for question 8, the predictive accuracy of the model was 0.44, the accuracy of the majority class model was 0.42, and the fit of the LR model was 0.24.

3.3 Experiment 3

Basing on experiment 2, background knowledge was extended by defining sets of related questions. Each set corresponds to one of the components of TPB (fig. 1) and

[3] http://potassco.sourceforge.net/

the topic of the question (recycling, contamination, etc.). Predicate *eco(S,Q,some|all)* represents that subject S answers 4 or 5 to *some* or *all* of the questions in set Q.

Results shows that predictive accuracy can be significantly increased by defining additional background knowledge. For example, the accuracy for question 8 was improved to 0.56. The model includes the following rule:

```
answers(S,q8,5) :- eco(S,int,some), eco(S,sn,some), eco(S,ac,some), answers(S,q47,5).
```

Meaning that a subject answers 5 to question 8, if she answers 4 or 5 to some of the questions related to INT, some of the questions related to *subjective norm* and *attitudes regarding contamination*, and 5 to question 47, about the PBC on waste management.

4 ILP+ASP for Human Reasoning and Decision Making

The Theory of the Adaptive Toolbox (TAT) [4] proposes that human reasoning can be modeled with *fast and frugal* heuristics. Most studies focus on the *paired comparison task*. In this task, a domain consists of *objects* that are ranked following a criterion, e.g. in the German Cities domain [4], 83 cities are ranked based on their population. Each object is described by a set of binary attributes (*cues*), e.g. *state capital?* The goal is to build a model that, for any set of two objects (*pair*), selects the highest ranking one.

The most commonly studied heuristic is *Take The Best* (TTB). For a pair, TTB selects a cue. If both objects have different values for it, then TTB selects the object with value 1. Else another cue is selected. Cues are searched in order of their *validities*. For a pair $\{A, B\}$ and a cue c_i, $validity(c_i) = p[A > B|c_i(A) = 1, c_i(B) = 0]$.

We report 2 experiments using the ILP+ASP method to build models for decision making, comparing them with TTB. In both experiments, the ILP system Aleph[4] was used, on the dataset of 17 domains proposed in [4]. For example, the German Cities domain has 83 cities described by 9 cues. No two cities have the same ranking, but some of them have the same cue values. The maximum accuracy of a model that selects cities based only on their cue values (testing on all data) will be in the range $[0.78, 0.84]$.

4.1 Representation

The learning target is *choose(P,A)*, where P is a pair of objects and A is the object with the highest ranking. Both experiments use a subset of the following background:

- *only(P,A,C,V)*: for pair P, city A is the *only* one that has value V for cue C.
- *both(P,C,V)*: *both* cities in P have the same value V for cue C.
- *same(A,B)*: objects A and B are the *same*.

4.2 Experiment 1

In this experiment, we show that ILP+ASP can learn alternative models to TTB, with similar accuracy, using the same background knowledge. Predicates *only* and *both* are used. After learning, an ASP theory is automatically created, sorting rules by accuracy i.e. the selected city will be the one selected by the rule with the higuest accuracy, disregarding other rules with less accuracy even if their body holds. The following rule:

[4] http://www.cs.ox.ac.uk/activities/machinelearning/Aleph/aleph

```
choose(P,A) :- only(P,A,soccerteam,1).
```

Means that in a pair where only one city has a soccer team, the city with it is selected.

Validation is performed for the 17 domains. For each run, cities are randomly split in two sets for training and testing, then all pairs are generated for each set. On average, for 180 runs per domain, TTB achieves an accuracy of 0.72, and ILP+ASP of 0.69.

4.3 Experiment 2

In this experiment, we show that ILP can learn rules that cannot be represented in TTB, outperforming it. The experiment is performed in the German Cities domain. All background is used in learning, and rules are also sorted by accuracy. For example,

```
choose(P,A) :- both(P,exposition,0), same(A,duisburg).
```

Means that *Duisburg* is selected if the other city does not have an exposition site.

For each run, all possible pairs (disregarding order) are generated for the 83 cities. Then, pairs are split into two sets of the same size. This setup makes rules about specific cities useful for new pairs. On average, for 125 runs, TTB achieves a mean predictive accuracy of $0.75(\pm 0.01)$, and ILP+ASP of $0.81(\pm 0.01)$.

5 Conclusions

We have introduced the ILP+ASP method for Psychology, and we have reported experiments on two fields of ExP: EnvP and HRDM. To our knowledge, there are few previous attempts to use symbolic methods in this area [4][2]. Reported experiments show that the ILP+ASP method can match or outperform alternative methods (LR, fast and frugal heuristics). Also, models built with the ILP+ASP method use rules near to natural language, can represent non-linear relations, and allow to perform extended reasoning tasks, problems not considered in the usual methods of ExP. As of future work we will apply ILP+ASP to other fields of Psychology, focusing on dynamic domains.

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