Towards Generating Explanations for ASP-Based Link Analysis using Declarative Program Transformations

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Abstract. The explication and the generation of explanations are prominent topics in artificial intelligence and data science, in order to make methods and systems more transparent and understandable for humans.

This paper investigates the problem of link analysis, specifically link prediction and anomalous link discovery in social networks using the declarative method of Answer set programming (ASP). Applying ASP for link prediction provides a powerful declarative approach, e.g., for incorporating domain knowledge for explicative prediction. In this context, we propose a novel method for generating explanations – as offline justifications – using declarative program transformations. The method itself is purely based on syntactic transformations of declarative programs, e.g., in an ASP formalism, using rule instrumentation.

We demonstrate the efficacy of the proposed approach, exemplifying it in an application on link analysis in social networks, also including domain knowledge.

Keywords: Explainable AI · Link Analysis · Prolog · Answer Set Programming

1 Introduction

Explicative approaches, i.e., transparent and explainable methods play an increasingly important role in the artificial intelligence and data science communities. General approaches for generating explanations in conjunction with a given method, or with its results are therefore important and relevant with a broad range of applications. In this paper, we focus on this problem in the context of logic programming approaches, in particular for answer set programming (ASP), cf. [1].

Specifically, we present a method for generating explanations for results of an answer set solver using declarative program transformations. For an answer set and its elements, we construct a trace of its derivation in terms of the applied rules and ground atoms, providing a justification [2]. It is important to note that the presented method, which relies on purely syntactic declarative program transformations, is in principle not restricted to ASP-based approaches, but could also be extended to further logic-based methods and theorem provers.

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We demonstrate the application of the proposed method on the problem of ASP-based link analysis, i.e., link prediction and anomaly analysis. Link prediction and (anomalous) link discovery are prominent methods in social network analysis (SNA), for which we have recently demonstrated the benefits of applying logic-based, particularly ASP-based approaches [3]. Essentially, link prediction aims to estimate the future link structure in a (social) network, while anomalous link discovery focuses on the identification of links in a network that deviate from a given model of normality, i.e., from expectations, or a specifically formalized model. In a case study, we show the efficacy of the proposed explanation method and its impact in the SNA domain, focussing on explanations for predicted/anomalous links. We apply ASP since it allows to specify interesting structures and patterns in a compact way. Due to its strength in including background knowledge by facts (and rules), link prediction approaches can be easily implemented and complemented if such background knowledge is available, cf. [3].

Our contributions are formulated as follows:
1. We propose a novel method for generating explanations on ASP-based formalisms using declarative program transformations.
2. We show the implementation of the method within the Declare [4] software system, targeting the Clingo system [5] as the applied answer set programming toolkit.
3. We demonstrate the efficacy of the presented method, i.e., its applicability and benefits of the proposed method in a case study using ASP-based link analysis for link prediction and anomalous link discovery, and obtaining respective explanations.

The rest of the paper is structured as follows: Section 2 discusses related work. After that, Section 3 outlines the proposed method for generating explanations. Next, Section 4 presents a case study on ASP-based link analysis. Finally, Section 5 concludes with a summary and outlines interesting directions for future work.

2 Related Work

Below, we discuss related work on answer set programming, before focusing on explanation and explanation. Finally, we briefly discuss related approaches on link prediction.

2.1 Answer Set Programming

Answer set programming (ASP) [6] is a declarative problem solving approach. Given a problem, ASP aims to find one or several possible solutions; these are the so-called answer sets, i.e., all possible sets of facts that are consistent with the facts stated earlier to the original problem, e.g., [7]. ASP is designed for NP-hard problems and finds its applications in large instances of industrial problems, since it offers a rich representation language and high performance solvers; some recent applications are listed in [9]. Some examples of ASP solvers that are considered to be efficient are Smolens [10], dlv [11], WASP [12], Clasp [13] and Clingo [5]. Clingo [3] itself combines a powerful grounder (Gringo) with Clasp (for solving) into an integrated system. For ease of use, and due to its efficiency (e.g., [14][15]), we utilized Clingo in the context of this paper. We assume that the reader has some background knowledge about ASP.

Available at: https://potassco.org/
2.2 Explication and Computing Explanations

Recently, the concept of explicative models and approaches has gained a strong momentum in artificial intelligence and data science, e.g., \cite{16,17} – aiming at transparent, interpretable, and explainable models in order to make the models and approaches more understandable to humans, in the idea of computational sensemaking \cite{18}. First approaches for generating explanations in the context of link prediction have been discussed by \cite{19}. In this paper, we extend on those approaches providing a specific implementation using ASP.

Furthermore, reconstructive explanations \cite{20}, also on several explanation dimensions \cite{16}, is an approach that constructs explanations by tracing back the steps of a system when constructing its output. In this sense, this forms an important basis of the approach proposed in this paper, since we construct explanations considering the specific answer set and rules that have fired, however targeting ASP in particular using a flexible declarative approach for program transformation. In the ASP-domain itself, constructing explanations and justifications is also a prominent topic \cite{21}, having emerged in recent years \cite{2,21,22}. Debugging techniques for ASP based on rewriting rules have been proposed, e.g., in \cite{23,24}. Also, justifications and justification trees \cite{2,21} of a derived answer set solution are related to our approach. We apply a similar technique for generating explanations, however, our method is different (and more general) in at least two ways: First, we do not only generate justifications, but extend on those by providing a user-specific selection on the given knowledge elements. Furthermore, our approach is more general, since we apply declarative program transformations that only perform syntactic transformations, and are not necessarily specific for ASP programs.

2.3 Link Analysis

Link analysis and mining encompasses several techniques and methods \cite{25}. In the context of this paper, we focus on link prediction and the anomalous link discovery.

The focus of link prediction is the dynamics and mechanisms in the creation of links between the parties in social networks \cite{25}. Such networks are typically represented as graphs, where nodes denote the parties, while edges model the links, i.e., the relationships between those parties. Then, the link prediction problem can be defined as the search to carefully predict edges that will be added to a given snapshot of a social network during a given interval, using network proximity measures of the nodes, i.e., based on how close the different nodes are in terms of their common set of neighbors in the network/graph. In \cite{3} we have presented the application of ASP for link prediction in social networks. In contrast to this approach, this paper does not focus on the link prediction by itself, but on the explanation or justification why a given result set (or a specific atom denoting a link) has been computed. For that reason, we apply ASP and declarative explication.

Anomalous link discovery \cite{27} aims at discovering anomalous links, e.g., using link prediction that are not highly likely, or that are in contrast to a given (reference) model \cite{3}. Compared to existing approaches, this paper does not present a new automatic method or approach for that. Instead, we present a simple model-based technique formalized using ASP, and show how to generate explanations for the anomalous links.
3 Method: Generating Explanations by Program Transformation

In this section, we describe our proposed method for generating explanations using declarative program transformations. We first give a bird’s eye view on the proposed approach, before we describe its implementation in detail.

3.1 Overview

We provide an overview shown in Figure 1, which depicts the workflow for the generation process. Please note, that in the process workflow, we indicate all steps performed by Declare with a “D” in red, while all processing steps involving Clingo are marked with a “C” in blue. We can roughly divide the process into two phases, i.e., program transformation and evaluation, as well as explanation generation and presentation.

Phase 1: Program Transformation and Evaluation by Instrumentation

1. We start with a Clingo Program which is processed by Declare into a Declare Program. This basically involves simple syntactic transformations.
2. The next steps for the more complex program transformation involves the syntactic transformation of the Declare program into an Extended Declare Program – by enriching the program as described below, using rule instrumentation. This program is then converted into an Extended Clingo Program.
3. Finally, this enriched program (including statements that allow the tracing and explanation generation) is evaluated by Clingo and results in the Extended Answer Set. It is important to note, that with a simple filtering operation, which removes all the extensions made by the Extended Clingo Program, we can obtain the Answer Set, which could also be obtained by direct evaluation of the Clingo Program by Clingo.

Phase 2: Incremental Explanation Generation and Presentation

1. We start with the Extended Answer Set, which is processed using Declare based on the answer set obtained from Clingo.
2. Based on that result, we can generate the Explanation using Declare. For that purpose, the trace information provided by the enriched program is utilized by Declare for constructing the explanation in reconstructive fashion.
3. Finally, the explanation is presented to the user as a Presentation. In this step, there is an incremental feedback loop with the explanation step, in order to include queries of the user, and to tailor the explanation and its presentation, respectively, to the context and interests of the user. For some more advanced queries, the explanation can also be refined, however, this requires a more comprehensive feedback loop back to the initial Declare Program. Then, this program can be extended and transformed accordingly to support more sophisticated explanation options like additional user constraints, domain knowledge, or summarization techniques. The latter can then be used, for example, for condensing the explanation.
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It is important to note, that we support an incremental explanation generation process. If the explanations are too complicated, or not sufficient, then we can refine the explanation, either by modifying the Declare program, or by extending/reducing the explanation given the answer set. This is indicated in Figure 1 by the feedback loop from Presentation to the Declare Program.

Furthermore, regarding presentation we can in principle provide the explanation in various form, cf. [16] for different explanation and presentation dimensions. However, one typical option is to use visualization, i.e., to potentially complement the textual justification by a visual representation in the form of a tree structure showing the dependencies of the facts and fired rules.

3.2 Program Transformation using Rule Instrumentation

Program transformations have also been used in [28] for computing the partial stable models of disjunctive logic programs with a theorem prover for stable models, which was specialized to normal logic programs and augmented with some further features in [29], and in the well-known magic sets method for deductive databases, cf. [30].

Our program transformation can be applied to Clingo rules with a head $A$, the positive body atoms $B_1, \ldots, B_n$, and the test body atoms $C_1, \ldots, C_m$ given as follows:
The test body atoms include all atoms which occur under meta-predicates such as default negation `not` or `count`. We assume, that this is rule number \( j \) of the Clingo program. The rule can contain variable symbols under certain conditions, which can be found in the Clingo literature, e.g. [5]. Assuming that the variable symbols occurring in the head and the positive body of the rule are \( X_1, \ldots, X_k \), then a further rule is constructed for recording that the rule has fired:

\[
\text{rule}\_\text{fired}(j, X_1, \ldots, X_k) :\leftarrow A, B_1, \ldots, B_n, C_1, \ldots, C_m.
\]

Observe, that the head atom \( A \) of the original Clingo rule becomes part of the body of the transformed Clingo rule. If \( P \) was the original Clingo program, and \( P_{\text{fired}} \) consists of the transformed Clingo rules, then we later evaluate the extended Clingo program \( P_{\text{ext}} = P \cup P_{\text{fired}} \) containing the original rules together with the transformed rules. We assume that the predicate symbol `rule_fired` does not occur in \( P \). Every answer set \( I_{\text{ext}} \) of \( P_{\text{ext}} \) corresponds to an answer set \( I \) of \( P \) extended by atoms for `rule_fired` indicating the ground instances of the rules that have fired.

E.g., assume that the following Clingo rule is rule number 6 with 2 positive body atoms followed by 3 test body atoms:

\[
\text{cn}_\text{lp}(Y, Z) :\leftarrow \text{node}(Y), \text{node}(Z), \not\text{edge}(Y, Z), Y!=Z, n=\#\text{count}\{X:\text{c}(X, Y, Z)\}.
\]

The positive body \( B_1, B_2 \) is `node(Y)`, `node(Z)`, and the test body atoms \( C_1, \ldots, C_3 \) are `not edge(Y, Z)`, `Y!=Z`, `n=\#\text{count}\{X:\text{c}(X, Y, Z)\}`. For given bindings of \( Y, Z \), the test atom `n=\#\text{count}\{X:\text{c}(X, Y, Z)\}` counts the number of constants \( X \), for which `c(X, Y, Z)` is true. Thus, the transformed rule is

\[
\text{rule}_\text{fired}(6, Y, Z) :\leftarrow \text{cn}_\text{lp}(Y, Z), \text{node}(Y), \text{node}(Z), \not\text{edge}(Y, Z), Y!=Z, n=\#\text{count}\{X:\text{c}(X, Y, Z)\}.
\]

Observe, that the variable symbol \( X \) is not part of the transformed rule, since it does not occur in the head or the positive body of the original Clingo rule.

Our approach is similar to the offline justifications of [21]. In addition, we can handle non-ground rules with variable symbols, and we can return the explanations and select a suitable subset for graphical presentation and visualization.

### 3.3 Generating Explanations

From the atoms `rule_fired(j, x_1, \ldots, x_k)` of the answer sets for the extended Clingo program \( P_{\text{ext}} \), it can be inferred which rule instances of the original Clingo program \( P \) have fired to support the answer set. For every derived atom `rule_fired(j, x_1, \ldots, x_k)`,
where \( j \) is a number and \( x_1, \ldots, x_k \) are constants, we know that the \( j \)-th rule of the original Clingo program \( \mathcal{P} \) fired with the instantiations \( X_i = x_i \) of the variable symbols occurring in the head or the positive body. From the substitution \( \theta = \{ X_i \mapsto x_i | 1 \leq i \leq k \} \) given by the derived atom \( \text{rule\_fired}(j, x_1, \ldots, x_k) \), we know that the head atom \( A\theta \) is also in the answer set, and that it is an element of the answer set of \( \mathcal{P} \). We can extract

\[
(A\theta) - \text{is\_supported\_by} - (A\theta :: B_1\theta, \ldots, B_n\theta, C_1\theta, \ldots, C_m\theta)
\]
as an explanation of \( A\theta \). If \( \text{rule\_fired}(7,1,3) \) was derived in the example above, then the following instance of rule 7 of the original Clingo program has fired to support \( \text{cn\_lp}(1,3) \):

```
cn\_lp(1, 3) :- node(1), node(3),
    not edge(1, 3), 1!=3, n=#count{X:c(X, 1, 3)}.
```

The variable symbol \( X \) is not bound, since it only occurs in the test atoms. We construct the explanation

```plaintext
(cn\_lp(1, 3) - is\_supported\_by -
    ( cn\_lp(1, 3) :- node(1), node(3),
        not edge(1, 3), 1!=3, n=#count{X:c(X, 1, 3)} ).
```

### 3.4 Presenting Explanations

The number of constructed explanations can be very large, as turned out in the case studies of Section 4. For a suitable visualization, we can query the set of explanations; e.g., we can select certain explanations \( (A\theta) - \text{is\_supported\_by} - \text{rule\_instance} \), such that the predicate symbol of the head \( A \) is in a suitable subset. Then, the explanations could also be visualized by dependency graphs.

### 4 Case Study: ASP-Based Link Analysis

In the following, we outline our method for link prediction using ASP. The main strength of ASP is its intuitive way to state a problem, also allowing to scale the problem up easily, and the availability of computationally powerful ASP solvers. For this study, the former two points are more relevant since for our application we utilize a relatively small data set in our case study. As an ASP solver, we use Clingo embedded in Python. The following example programs are stratified; i.e., there is no recursion through test atoms (e.g., negated atoms or count atoms). In more complicated examples, e.g., including more declarative background knowledge, however, recursion could be used.

As introduced above, link prediction aims at inferring the (future) link structure of a network, e.g., based on time intervals, such that the network used for prediction uses the links contained in the first time interval \( T_1 \) while the network used for testing uses the links contained in the second (subsequent) time interval \( T_2 \), cf. Figure 2.
As a simple example, the graph $G$ shown in Figure 2 represents interaction between actors at an event, split into two time frames. Then, we utilize the information given in time interval 1, i.e., the green edges, in order to infer the link structure in time interval 2, i.e., the violet edges. In particular, we aim at predicting those links given the information on time interval 1.

A quite simple but usually quite effective approach for link prediction is to consider the number of common neighbors of two nodes as a ranking for predicting a link. In the following, we will utilize that simple common neighbor predictor in an ASP implementation. Besides a simple graph $G_1$, we can also extend the approach to a bipartite graph $A$ used as background information, for predicting links, see Figure 3 for an example.

Rules can be created in such a way that for a constant $n$ (a threshold), where $\Gamma_G(x)$ stands for the neighborhood of node $x$ in a graph $G$, $E_{2\text{pred}}$ stands for the predicted edges for $T_2$:

$$
\forall u, v \in V \mid (u, v) \notin E_1, \ |\Gamma_A(u) \cap \Gamma_A(v)| = n \implies \\
\forall x \in \Gamma_{G_1}(u) \setminus \Gamma_{G_1}(v) \mid (x, v) \in E_{2\text{pred}} \land \forall y \in \Gamma_{G_1}(v) \setminus \Gamma_{G_1}(u) \mid (x, u) \in E_{2\text{pred}}.
$$

Then, given $G_1$ and $A$, we can predict links for time interval 2, denoted as $E_{2\text{pred}}$.

4.1 Example: Link Prediction

Below, we will first illustrate our approach for link prediction via a small hypothetical example. The example data is visualized in Figure 3.

The Clingo code corresponding to the example in Figure 3 describes two symmetric graphs, the interaction graph and the attributive graph, by giving the edges and some symmetry rules. The computed answer set compares the predicted links with some expected test links. The first part of the Clingo program defines two constants and the nodes and edges of the graphs:

```clingo
#const n=1.
#const n_attrib=1.
```
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Fig. 3: Example: Interaction graph $G_1$, and attributive graph $A$, where $f$ and $m$ denote attributes.

% Interaction Graph: Nodes
define node(1..4).
% Edges, first time interval
define edge(1, 2). edge(2, 3).
% Edges, second time interval (test set)
define test(1,3). test(2,4).

% Attributive Graph: Nodes and Edges
define node_attrib(2). node_attrib(4).
define node_attrib(f). node_attrib(m).
define edge_attrib(2, m). edge_attrib(4, m).

% The edge relations are made symmetric,
% such that they correspond to undirected graphs.
define edge(Y, X) :- edge(X, Y).
define edge_attrib(Y, X) :- edge_attrib(X, Y).
define test(Y, X) :- test(X, Y).

The link prediction is accomplished by the second part of the Clingo program:

% X is a common neighbor of the unconnected Y and Z.
define c(X, Y, Z) :- edge(X, Y), edge(X, Z),
                   not edge(Y, Z), Y!=Z.
define c_attrib(X, Y, Z) :-
                   edge_attrib(X, Y), edge_attrib(X, Z),
                   not edge_attrib(Y, Z), Y!=Z.
% A link is predicted, when there is one common neighbor
% in the interaction/attributive graph (c/c_attrib).
define cn_lp(Y, Z) :- node(Y), node(Z),
                   not edge(Y, Z), Y!=Z,
                   n=#count{X:c(X, Y, Z)}.
define cn_lp(Y, Z) :- node(Y), node(Z),
not edge(Y, Z), Y!=Z,
 n_attrib=#count{X:c_attrib(X, Y, Z)}.

% match compares the predicted links with the test links
match(X, Y) :- test(X, Y), cn_lp(X, Y).

In the following, we show a part of the computed answer set, as requested by the show statements in the clingo code. The facts for match show that the predicted links (predicate cn_lp) exactly match the expected links (predicate test) of the test set.

\[
\text{cn\_lp}(1,3) \quad \text{cn\_lp}(3,1) \quad \text{cn\_lp}(2,4) \quad \text{cn\_lp}(4,2) \\
\text{match}(1,3) \quad \text{match}(3,1) \quad \text{match}(2,4) \quad \text{match}(4,2)
\]

The additionally computed facts of the answer set of the extended clingo program show that \text{cn\_lp}(2,4) and \text{cn\_lp}(4,2) were generated from rule 6 (line 1 below), whereas \text{cn\_lp}(1,3) and \text{cn\_lp}(3,1) were generated from rule 7 (line 2 below). The match facts were all generated from rule 14 (lines 3 and 4 below).

\[
\begin{align*}
\text{rule\_fired}(6,2,4) & \quad \text{rule\_fired}(6,4,2) \\
\text{rule\_fired}(7,1,3) & \quad \text{rule\_fired}(7,3,1) \\
\text{rule\_fired}(14,1,3) & \quad \text{rule\_fired}(14,3,1) \\
\text{rule\_fired}(14,2,4) & \quad \text{rule\_fired}(14,4,2)
\end{align*}
\]

For generating the explanations, we then apply our proposed method. This results in the following explanations indicating two ground instances of rule 7 deriving the facts \text{cn\_lp}(1,3) and \text{cn\_lp}(3,1), respectively, and two ground instances of rule 14 deriving the facts \text{match}(1,3) and \text{match}(3,1), respectively:

\[
\begin{align*}
\text{cn\_lp}(1,3)-\text{is\_supported\_by}-
& (\text{cn\_lp}(1,3)-[\text{node}(1),\text{node}(3)]-
\quad [\text{not} \text{ edge}(1,3), \text{1!}=3, \text{n}=\text{#count}\{X:\text{c}(X,1,3)\}]) \\
\text{cn\_lp}(3,1)-\text{is\_supported\_by}-
& (\text{cn\_lp}(3,1)-[\text{node}(3),\text{node}(1)]-
\quad [\text{not} \text{ edge}(3,1), \text{3!}=1, \text{n}=\text{#count}\{X:\text{c}(X,3,1)\}]) \\
\text{match}(1,3)-\text{is\_supported\_by}-
& (\text{match}(1,3)-[\text{test}(1,3),\text{cn\_lp}(1,3)]-[]) \\
\text{match}(3,1)-\text{is\_supported\_by}-
& (\text{match}(3,1)-[\text{test}(3,1),\text{cn\_lp}(3,1)]-[])
\end{align*}
\]

The analogous explanations of \text{cn\_lp}(2,4) and \text{cn\_lp}(4,2) are not shown.

For presentation, we show the computed answer set $I$ and we visualize its explanation, i.e., its justification by a tree structure $T$; see Figure 4. All body atoms are relevant for the explanations; the positive body atoms lead to subtrees, whereas the test body atoms have only been tested in $I$ (which was assured by the atoms for \text{rule\_fired}).
Fig. 4: Example: Presentation of the generated explanation. The justification of the answer set is represented by a tree structure.

4.2 Example: Anomalous Link Discovery

This section describes a more complex example. Here, we are not only interested in the link prediction, but also in anomalous link discovery. As discussed above, anomalous link discovery aims at discovering anomalous links that are in contrast to a given (reference) model [3]. In our example, we can consider a given network, as a reference model for interaction behavior, which we can then compare to the predicted interaction behavior. Using declarative programming and particularly answer set programming, it is very simple to implement that.

First, we demonstrate a case where domain knowledge formalized in a network is used together with past interactions to predict future links, for a bipartite graph. Consider Figure 5. The bipartite graph $A$ represents the choices of the attributive information provided as background knowledge. The nodes $s_1, s_2, s_3, s_4, s_5$ represent students, and the nodes $f, m$ represent their gender ($f$: female, $m$: male). The nodes $dsg, csai$ are standing for the master programs the students are enrolled to, e.g., “Cognitive Science and Artificial Intelligence” or “Data Science for Business and Governance”.

Above, we have described how to connect similar disconnected vertices, where similarity was determined by the number of common neighbors. Here, similarity is defined the same way, but we do not connect similar disconnected vertices; we predict new links for each based on the neighborhood of the other.

In Figure 5, a pair of bipartite graphs are shown on the top row. The graph $A$ has a set of vertices partitioned into students $\{s_1, \ldots, s_5\}$, and a set of attributes represented by nodes $\{csai, dss, f, m\}$. Graph $G_1$ has vertices partitioned into students $\{s_1, \ldots, s_5\}$, and companies $\{c_1, \ldots, c_5\}$. This graph captures only the interactions between the students and companies. The intuition is that similar students have similar interests. In the second row, we see the projections of the graphs on students $(P_A, P_{G_1})$. A projection graph for a bipartite graph is a weighted graph on the set of vertices on one of the partitions, where the weight of the edges is determined by the number of common neighbors. We highlight the edges where the weight is 2, and assume the students these edges are joining as similar. Then finally, in the last row we see the graph showing the predicted
links, between the students and the companies. For both graphs $A, G_1$, for a pair of similar vertices $s_i, s_j, (i, j \in \{1, 2, 3, 4, 5\}, i \neq j)$ we predict a link between $s_i, c_k$ if $(s_j, c_k)$ is an edge in $G_1$, and $(s_i, c_k)$ is not. These two similarity measures based on two different graphs $A, G_1$ imply different sets of predicted links say $G_{(Pr,A)}, G_{(Pr,G_1)}$.

Fig. 5: Comparing links predicted via background knowledge ($A$) and past links ($G_1$).

The ASP code below calculates the predicted links as well as distinguishes the sets $G_{(Pr,A)} \setminus G_{(Pr,G_1)}$, $G_{(Pr,G_1)} \setminus G_{(Pr,A)}$ and $G_{(Pr,G_1)} \cap G_{(Pr,A)}$ for anomaly analysis purposes. We omit the first part of the Clingo file. Constants are given as: $n=2$, $n\text{\_attrib}=2$ (2 common neighbors, see below). Facts for the networks/graphs are defined as follows:

- node\_s (X): the 5 yellow nodes of $G_1$,
- edges (X, Y): the 13 edges of $G_1$,
- edge\_attrib (X, Y): the 8 edges of $A$. 
The graphs are undirected, which is ensured by additional rules for the edge relations edge/2 and edge_attrib/2. X is a common neighbor of Y and Z:

\[
\begin{align*}
  c(X, Y, Z) & : - \text{edge}(X, Y), \text{edge}(X, Z), \\
  & \quad \text{node_s}(X), \text{node_s}(Y), \text{node_s}(Z), Y!\neq Z. \\
  c\_attrib(X, Y, Z) & : - \\
  & \quad \text{edge_attrib}(X, Y), \text{edge_attrib}(X, Z), \\
  & \quad \text{node_s_attrib}(X), \text{node_s_attrib}(Y), \\
  & \quad \text{node_s_attrib}(Z), Y!\neq Z.
\end{align*}
\]

Two students are similar of type 1/2 (similar_1/2, similar_2/2), if they have two common neighbors in the interaction/attribute graph:

\[
\begin{align*}
  \text{similar}_1(Y, Z) & : - \text{node_s}(Y), \text{node_s}(Z), \\
  & \quad \text{not} \ \text{edge}(Y, Z), Y!\neq Z, \\
  & \quad n=\#\text{count}\{X: c(X, Y, Z)\}. \\
  \text{similar}_2(Y, Z) & : - \text{node_s_attrib}(Y), \text{node_s_attrib}(Z), \\
  & \quad \text{not} \ \text{edge_attrib}(Y, Z), Y!\neq Z, \\
  & \quad n\_attrib=\#\text{count}\{X: c\_attrib(X, Y, Z)\}.
\end{align*}
\]

We consider pairs of similar vertices and the nodes that are adjacent to one but not the other and predict a link based on that.

\[
\begin{align*}
  \text{lp}_1(X, Y) & : - \text{similar}_1(Y, Z), \text{edge}(X, Z), \text{not} \ \text{edge}(X, Y). \\
  \text{lp}_2(X, Y) & : - \text{similar}_2(Y, Z), \text{edge}(X, Z), \text{not} \ \text{edge}(X, Y). \\
  \text{common}(X, Y) & : - \text{lp}_1(X, Y), \text{lp}_2(X, Y). \\
  \text{diff}_12(X, Y) & : - \text{lp}_1(X, Y), \text{not} \ \text{common}(X, Y). \\
  \text{diff}_21(X, Y) & : - \text{lp}_2(X, Y), \text{not} \ \text{common}(X, Y).
\end{align*}
\]

From the Clingo program, the following answer set is computed:

\[
\begin{align*}
  \text{common}(c3, s3) & \quad \text{common}(c5, s1) \quad \text{common}(c2, s4) \\
  \text{diff}_12(c1, s5) & \quad \text{diff}_21(c4, s4) \\
  \text{diff}_21(c5, s2) & \quad \text{diff}_21(c3, s2) \\
  \text{lp}_1(c1, s5) & \quad \text{lp}_1(c3, s3) \quad \text{lp}_1(c5, s1) \quad \text{lp}_1(c2, s4) \\
  \text{lp}_2(c3, s3) & \quad \text{lp}_2(c4, s4) \quad \text{lp}_2(c2, s4) \\
  \text{lp}_2(c5, s1) & \quad \text{lp}_2(c5, s2) \quad \text{lp}_2(c3, s2)
\end{align*}
\]

When we perform our proposed method, selecting diff_12, diff_21, lp_1 and lp_2 as predicates, we obtain an extended answer set of size 144, which already indicates the (large) size of the explanation. When generating the explanation on this extended answer set, we obtain a set of size 136 accordingly. This already shows the complexity, since a naive visualization approach for presentation would result in a presentation that is not understandable. Therefore, according selection on specific instances and predicates needs to be performed by the user, in an incremental fashion.
5 Conclusions

In this paper, we have proposed a novel method for generating explanations in an incremental process using declarative program transformations. Since the method itself is purely based on syntactic transformations of declarative programs, the method enables in principle a general approach. However, in the context of this paper we exemplified the approach by focusing on answer set programming – as a prominent tool for declarative programming. Our implementation itself is embedded into the Declare software toolkit. For the program evaluation we directly connect to Clingo. We have exemplified the application and efficacy of the proposed approach in the context of link analysis, i.e., link prediction and anomalous link discovery for social networks. Our exemplary results indicate that the method performs well for obtaining explanations and according presentations which can also be incrementally refined.

For future work, we aim to extend the approach towards knowledge-based automatic refinement methods, also taking into account more complex (and richer) data representations, e.g., in the field of complex interaction networks [31].

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