

# Datalog and Answer Set Programming (part 2)

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# Positive Datalog: reasoning

# Reasoning in positive Datalog

Basic reasoning task: construction of  $MM(P)$

Derived reasoning task: ground atom entailment

- Given a Datalog program  $P$  and a ground atom  $\alpha$ , we say that  $P$  **entails**  $\alpha$  if  $\alpha \in MM(P)$

# Immediate consequence operator

Given a ground positive Datalog program  $P$ , the **immediate consequence operator for  $P$** , denoted as  $T_P$ , is the function over the domain of interpretations for  $P$  defined as follows:

$$T_P(I) = \{ \alpha \mid \text{there exists a rule } \alpha :- \beta_1, \dots, \beta_n \text{ in } P \text{ such that } \{ \beta_1, \dots, \beta_n \} \subseteq I \}$$

The **least fixed point** of the function  $T_P$  is the minimal interpretation  $I$  such that  $T_P(I) = I$ .

# Immediate consequence operator

Example: let  $P$  be the following ground program:

$r(a) :- p(a).$

$r(b) :- q(b).$

$p(a).$

Then:

$$T_P(\{\}) = \{ p(a) \}$$

$$T_P(\{ p(a) \}) = \{ p(a), r(a) \}$$

$$T_P(\{ p(a), r(a) \}) = \{ p(a), r(a) \} \text{ (least fixed point)}$$

$$T_P(\{ q(b) \}) = \{ p(a), r(b) \}$$

$$T_P(\{ p(a), r(b) \}) = \{ p(a), r(a) \}$$

$$T_P(\{ p(a), q(b), r(b) \}) = \{ p(a), r(a), r(b) \}$$

$$T_P(\{ p(a), r(a), r(b) \}) = \{ p(a), r(a), r(b) \} \text{ (fixed point)}$$

$$T_P(\{ p(a), q(b), r(a), r(b) \}) = \{ p(a), r(a), r(b) \}$$

# Operational semantics

Property: For every ground positive Datalog program  $P$ , the immediate consequence operator  $T_P$  has a unique least fixed point that coincides with  $MM(P)$ .

The above property provides an **operational semantics** for ground positive Datalog program.

In fact, from the previous property we can immediately derive the following algorithm for the computation of the minimal model of a ground positive program  $P$ .

# Naive evaluation

Algorithm **naive-evaluation**

Input: ground positive Datalog program  $P$

Output:  $MM(P)$

begin

  let  $I' = \{\}$ ;

  repeat

    let  $I = I'$ ;

    compute  $I' = T_P(I)$

  until  $I' == I$ ;

  return  $I$

end

This algorithm executes at most  $k+1$  iterations of the repeat-until loop, where  $k$  is the number of rules of  $P$

# Reasoning over non-ground programs

The naive evaluation algorithm could be used also for non-ground programs:

1. First, compute the ground program  $\text{ground}(P)$ ;
2. Then, execute the naive evaluation algorithm on  $\text{ground}(P)$ .

The interpretation returned by the algorithm is the minimal model of  $\text{ground}(P)$  and therefore the minimal model of  $P$ .

We now present the **semi-naive evaluation** algorithm, which optimizes the naive evaluation.



# Delta predicates

Idea of the optimization: reformulate the program  $P$  in a way such that the immediate consequence operator  $T_p$  can derive a ground atom only if its derivation depends on at least one ground atom derived in the previous application of  $T_p$  in the algorithm.

This minimizes redundant derivations, i.e., repeated derivations of the same ground atoms in different applications of  $T_p$ .

This idea is realized by introducing **delta** versions of the IDB predicates of the program, and rewriting the program through the usage of such delta predicates.

# Delta predicates

In the algorithm, the extension of a  $\Delta$ -predicate  $\Delta p$  represents the ground atoms relative to predicate  $p$  derived by the **previous** application of the immediate consequence operator.

A second set of  $\Delta'$ -predicates is used in rule heads: in this way, each  $\Delta'p$  represents the ground atoms relative to predicate  $p$  derived by the **current** application of the immediate consequence operator.

# $\Delta$ -transformation of a rule

In the following, we denote a rule  $r$  of a positive program  $P$  as follows:

$$\alpha :- \beta_1, \dots, \beta_k, \gamma_1, \dots, \gamma_h$$

where every  $\beta_i$  is an IDB-atom (i.e. an atom in which an IDB predicate of  $P$  occurs), and every  $\gamma_i$  is an EDB-atom

Given a rule  $r$  of the above form,  $\Delta r$  is the following set of  $k$  rules:

$$\Delta'\alpha :- \Delta\beta_1, \beta_2, \dots, \beta_k, \gamma_1, \dots, \gamma_h$$

$$\Delta'\alpha :- \beta_1, \Delta\beta_2, \dots, \beta_k, \gamma_1, \dots, \gamma_h$$

...

$$\Delta'\alpha :- \beta_1, \beta_2, \dots, \Delta\beta_k, \gamma_1, \dots, \gamma_h$$

where:

- if  $\beta_i = r(t_1, \dots, t_n)$ , then  $\Delta\beta_i$  denotes the atom  $\Delta r(t_1, \dots, t_n)$
- if  $\alpha = r(t_1, \dots, t_n)$ , then  $\Delta'\alpha$  denotes the atom  $\Delta' r(t_1, \dots, t_n)$

# $\Delta$ -transformation of a rule

Therefore, if the body of  $r$  contains  $k$  atoms with IDB predicates,  $\Delta r$  contains  $k$  rules (for every such atom there is a rule where the delta predicate is used in such an atom instead of the standard predicate)

# $\Delta$ -transformation of a rule

Example: let  $IDB = \{r/1, s/2\}$ ,  $EDB = \{p/2\}$ , and let  $P$  be as follows:

$r(X) :- s(X, Y), p(X, Y). \text{ [r1]}$

$s(X, Y) :- p(X, Y), p(Y, Z). \text{ [r2]}$

$s(X, Y) :- s(X, Z), r(Y), p(Y, X). \text{ [r3]}$

$p(a). \text{ [r4]}$

Then:

$\Delta r1 = \{ \Delta' r(X) :- \Delta s(X, Y), p(X, Y). \}$

$\Delta r2 = \{ \}$

$\Delta r3 = \{ \Delta' s(X, Y) :- \Delta s(X, Z), r(Y), p(Y, X). \}$

$\Delta' s(X, Y) :- s(X, Z), \Delta r(Y), p(Y, X). \}$

$\Delta r4 = \{ \}$

# $\Delta$ -transformation of a program

Given a positive Datalog program  $P$ , the  $\Delta$ -transformation of  $P$ , denoted as  $\Delta P$ , is the program obtained as the union of all the sets  $\Delta r$  of every rule  $r$  in  $P$ .

Example (contd.):

$$\begin{aligned}\Delta P &= \Delta r1 \cup \Delta r2 \cup \Delta r3 \cup \Delta r4 = \\ &= \{ \Delta' r(X) :- \Delta s(X, Y), p(X, Y). \\ &\quad \Delta' s(X, Y) :- \Delta s(X, Z), r(Y), p(Y, X). \\ &\quad \Delta' s(X, Y) :- s(X, Z), \Delta r(Y), p(Y, X). \} \end{aligned}$$

The algorithm then computes the immediate consequence operator  $T_{\Delta P}$  of  $\Delta P$ , treating both  $\Delta$ -predicates and  $\Delta'$ -predicates like all other standard predicates.

# Semi-naive evaluation

Algorithm **semi-naive-evaluation**

Input: positive Datalog program  $P$

Output:  $MM(P)$

begin

  let  $I = EDB(P)$ ; //(EDB(P) is the set of facts in  $P$ )

  compute  $I' = T_P(I)$ ;

  if  $I = I'$  then return  $I$ ;

$\Delta I = \{ \Delta' \alpha \mid \alpha \in I' - I \}$ ;

  repeat

    let  $I = I \cup \{ \alpha \mid \Delta' \alpha \in \Delta' I \}$ ;

    let  $\Delta I = \{ \Delta \alpha \mid \Delta' \alpha \in \Delta' I \}$ ;

    let  $\Delta' I = T_{\Delta P}(I \cup \Delta I)$

  until  $\Delta' I = \{ \}$ ;

  return  $I$

end

# Example of execution of the algorithm

Let P be the following positive Datalog program:

$r(X, Y) :- p(X, Y). \text{ [r1]}$

$r(X, Z) :- p(X, Y), r(Y, Z). \text{ [r2]}$

$s(X, Y) :- r(Y, X). \text{ [r3]}$

$p(a, b).$

$p(b, c).$

$p(c, d).$

- The initial value of I is the set of facts of P, i.e.  
 $\{ p(a, b), p(b, c), p(c, d) \}$
- Then,  $I' = T_P(I) = I \cup \{ r(a, b), r(b, c), r(c, d) \}$  (applying r1)
- So,  $\Delta I = \{ \Delta r(a, b), \Delta r(b, c), \Delta r(c, d) \}$



## Example (contd.)

- Then, the algorithm executes the repeat-until loop for the first time, obtaining:

$$\begin{aligned} I &= I \cup \{ r(a, b), r(b, c), r(c, d) \} \\ \Delta I &= \{ \Delta r(a, b), \Delta r(b, c), \Delta r(c, d) \} \\ \Delta' I &= T_{\Delta P}(I \cup \Delta I) = \\ &= \{ \Delta' r(a, c), \Delta' r(b, d), \Delta' s(b, a), \Delta' s(c, b), \Delta' s(d, c) \} \\ &\quad \text{(applying r2 and r3)} \end{aligned}$$

- Then, the algorithm executes the repeat-until loop for the second time, obtaining:

$$\begin{aligned} I &= I \cup \{ r(a, c), r(b, d), s(b, a), s(c, b), s(d, c) \} \\ \Delta I &= \{ \Delta r(a, c), \Delta r(b, d), \Delta s(b, a), \Delta s(c, b), \Delta s(d, c) \} \\ \Delta' I &= T_{\Delta P}(I \cup \Delta I) = \\ &= \{ \Delta' r(a, d), \Delta' s(c, a), \Delta' s(d, b) \} \quad \text{(applying r2 and r3)} \end{aligned}$$

## Example (contd.)

- Then, the algorithm executes the repeat-until loop for the third time, obtaining:

$$I = I \cup \{ r(a, d), s(c, a), s(d, b) \}$$

$$\Delta I = \{ \Delta r(a, d), \Delta s(c, a), \Delta s(d, b) \}$$

$$\Delta' I = T_{\Delta P}(I \cup \Delta I) = \{ \Delta' s(d, a) \} \text{ (applying r3)}$$

- Then, the algorithm executes the repeat-until loop for the fourth time, obtaining:

$$I = I \cup \{ s(d, a) \}$$

$$\Delta I = \{ \Delta s(d, a) \}$$

$$\Delta' I = T_{\Delta P}(I \cup \Delta I) = \{ \}$$

## Example (contd.)

- Since  $\Delta'I$  is empty, the algorithm exits the repeat-until loop and terminates returning the interpretation I, that is, the set

$$\{ p(a, b), p(b, c), p(c, d), r(a, b), r(b, c), r(c, d), r(a, c), r(b, d), \\ s(b, a), s(c, b), s(d, c), r(a, d), s(c, a), s(d, b), s(d, a) \}$$

Such an interpretation I is the minimal model of P.