# A Quasi-Metric for Machine Learning

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**Abstract.** The subsumption relation is crucial in the Machine Learning systems based on a clausal representation. In this paper we present a class of operators for Machine Learning based on clauses which is a characterization of the subsumption relation in the following sense: The clause  $C_1$  subsumes the clause  $C_2$  iff  $C_1$  can be reached from  $C_2$  by applying these operators. In the second part of the paper we give a formalization of the closeness among clauses based on these operators and an algorithm to compute it as well as a bound for a quick estimation.

#### 1 Introduction

In a Machine Learning system based on clausal logic, the main operation lies on applying an operator to one or more clauses with the hope that the new clauses give a better classification for the training set. This generalization must fit into some relation of order on clauses or sets of clauses. The usual orders considered in Machine Learning based on clauses are the subsumption order, denoted by  $\succeq$ , and the implication order  $\models$ . Most of the systems use the subsumption order to carry out the generalization, in spite of the implication order is stronger, i.e., if the clause  $C_1$  subsumes the clause  $C_2$ ,  $C_1 \succeq C_2$ , then  $C_1 \models C_2$ . The reason for choosing the subsumption order is easy: The subsumption between clauses is decidable, whereas the implication order is not [10].

Therefore the subsumption between clauses is the basic relation of order in the generalization processes in Machine Learning with clausal representation, but how is this generalization carried out? The subsumption relation was presented by G. Plotkin [7]. In his study about the lattice structure induced by this relation on the set of clauses, he proved the existence of the least general generalization of two clauses under subsumption and defined the least generalization under relative subsumption. Both techniques are the basis of successful learning systems on real-life problems.

Later, different classes of operators on clauses, the so-called refinement operators, were studied by Shapiro [9], Laird [4] and Nienhuys-Cheng and de Wolf [11] among others. In their works, the emphasis is put on the specialization operators, which are operators such that the obtained clause is implied or subsumed by the

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original clause, and the generalization operators are considered the dual of the first ones.

In this paper we present *new* generalization operators for clausal learning, the Learning Operators under Subsumption (LOS) which allow us to generalize clauses in the subsumption order, i.e., if C is a clause,  $\{\Delta/x\}$  is a LOS and  $C\{\Delta/x\}$  is the output clause, then  $C\{\Delta/x\}$  subsumes C.

This property states that the LOS are operators of generalization under subsumption in the set of clauses, but the main property of these operators is that the LOS represent a characterization by operators of the subsumption relation between clauses in the following sense: If  $C_1$  and  $C_2$  are clauses,  $C_1$  subsumes  $C_2$  if and only if there exists a finite sequence (a chain) of LOS  $\{\Delta_1/x_1\},\ldots,\{\Delta_n/x_n\}$  such that

$$C_1 = C_2\{\Delta_1/x_1\} \dots \{\Delta_n/x_n\}$$

If  $C_1$  subsumes  $C_2$ , we know that the set of chains of LOS from  $C_2$  to  $C_1$  is not empty, but in general the set has more than one element.

The existence of a non-empty set of chains gives us the idea for a formalization of *closeness* among clauses as the length of the shortest chain from  $C_2$  to  $C_1$ , if  $C_1$  subsumes  $C_2$ , and infinity otherwise.

This mapping, which will be denoted by dc, is the algebraic expression of the subsumption order: for every pair of clauses,  $C_1$  and  $C_2$ ,  $C_1$  subsumes  $C_2$  if and only if  $dc(C_2, C_1)$  is finite. Since the subsumption order is not symmetric, the mapping dc is not either. Therefore dc is not a metric, but a quasi-metric.

Finally, dc is computable. We give in this paper an algorithm which calculates the quasi-distance between two clauses and present a bound which allows to estimate the closeness between clauses under the hypothesis of subsumption.

### 2 Preliminaries

From now on, we will consider some fixed first-order language  $\mathcal{L}$  with at least one function symbol. Var, Term and Lit are, respectively, the sets of variables, terms and literals of  $\mathcal{L}$ . A clause is a finite set of literals, a program is a finite set of clauses and  $\mathbb{C}$  is the set of all clauses.

A substitution is a mapping  $\theta: S \to Term$  where S is a finite set of variables such that  $(\forall x \in S)[x \neq \theta(x)]$ . We will use the usual notation  $\theta = \{x/t : x \in S\}$ , where  $t = \theta(x)$ ,  $Dom(\theta)$  for the set S and  $Ran(\theta) = \bigcup \{Var(t) : x/t \in \theta\}$ . A pair x/t is called a binding. If A is a set, then |A| is the cardinal of A and  $\mathcal{P}A$  its power set. We will denote by  $|\theta|$  the number of bindings of the substitution  $\theta$ . The clause C subsumes the clause D,  $C \succeq D$ , iff there exists a substitution  $\theta$  such that  $C\theta \subseteq D$ .

A position is a non-empty finite sequence of positive integers. Let  $\mathbb{N}^+$  denote the set of all positions. If  $t = f(t_1, \dots, t_n)$  is an atom or a term,  $t_i$  is the term at position i in t and the term at position i in t is s if s is at position u in  $t_i$ . Two positions u and v are independent if u is not a prefix of v and vice versa. A set

of positions P is independent if  $(\forall u, v \in P)[u \neq v \Rightarrow u \text{ and } v \text{ are independent}]$  and the set of all positions of the term t in L will be denoted by Pos(L,t). If t is a term (resp. an atom), we will denote by  $t[u \leftarrow s]$  the term (resp. the atom) obtained by grafting the term s in t at position u and, if L is a literal, we will write  $L[P \leftarrow s]$  for the literal obtained by grafting the term s in L at the independent set of positions P.

## 3 The Operators

In the generalization process, when a program P is too specific, we replace it by P' with the hope that P' covers the examples better than P. The step from P to P' is usually done by applying an operator to some clause P of P. These operators can be defined as mappings from  $\mathbb C$  to  $\mathbb C$  where  $\mathbb C$  is the set of clauses of the language. Before giving the definition of the operator, we will give some intuition with an example.

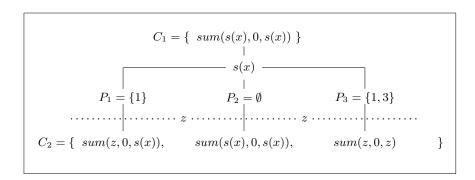


Fig. 1. Example of generalization

Consider the one-literal clause  $C_1 = \{L\}$  with L = sum(s(x), 0, s(x)). In order to generalize it with respect to the subsumption order, we have to obtain a new clause  $C_2$  such that there exists a substitution  $\theta$  verifying  $C_2\theta \subseteq C_1$ . For that, we firstly choose a term t in L, say t = s(x), then we choose several subsets of Pos(L,t), e.g.  $P_1 = \{1\}, P_2 = \emptyset, P_3 = \{1,3\}$  and a variable not occurring in L, say z, and finally we build the clause  $C_2 = \{L[P_i \leftarrow z] \mid i = 1,2,3\} = \{sum(z,0,s(x)), sum(s(x),0,s(x)), sum(z,0,z)\}$ . Obviously  $\theta = \{z/s(x)\}$  satisfies  $C_2\theta \subseteq C_1$  (see Fig. 1).

If the clause has several literals, for example,  $C_1 = \{L_1, L_2, L_3\}$ , with  $L_1 = num(s(x))$ ,  $L_2 = less\_than(0, s(x))$  and  $L_3 = less\_than(s(x), s(s(x)))$ , the operation is done with all literals simultaneously. First, the same term is chosen in every literal of  $C_1$ , say t = s(x). Then, for each literal  $L_i \in C_1$ , some subsets of  $Pos(L_i, t)$  are chosen, e.g.,

$$P_{1}^{*} = \{ \emptyset, \{1\} \} \subseteq PPos(L_{1}, t)$$

$$P_{2}^{*} = \emptyset \subseteq PPos(L_{2}, t)$$

$$P_{3}^{*} = \{ \{1, 2 \cdot 1\}, \{1\} \} \subseteq PPos(L_{3}, t)$$

After taking a variable which does not occur in  $C_1$ , say z, the following sets are built

$$\begin{array}{ll} L_1 & \xrightarrow{P_1^*} & \{num(s(x)), num(z)\} \\ L_2 & \xrightarrow{P_2^*} & \emptyset \\ L_3 & \xrightarrow{P_3^*} & \{less\_than(z, s(z)), less\_than(z, s(s(x)))\} \end{array}$$

Finally, the clause  $C_2$  is the union of these sets, i.e.,

$$C_2 = \{num(s(x)), num(z), less\_than(z, s(z)), less\_than(z, s(s(x)))\}$$

and  $C_2\{z/s(x)\}\subseteq C_1$ . In our general description, we will begin with a study of the relations between substitutions and grafts.

**Definition 1.** Let L be a literal and t a term. The set of positions P is called compatible with the pair  $\langle L, t \rangle$  if  $P \subseteq Pos(L, t)$ .

**Definition 2.** Let  $P^*$  be a set whose elements are sets of positions. Let L be a literal and t a term.  $P^*$  is called compatible with the pair  $\langle L, t \rangle$  if every element of  $P^*$  is compatible with  $\langle L, t \rangle$ 

For example, if L = sum(s(x), 0, s(x)) and t = s(x), then  $P_1 = \{1\}$ ,  $P_2 = \emptyset$  and  $P_3 = \{1,3\}$  are compatible with  $\langle L,t\rangle$  and  $P_4 = \{1\cdot 1,2\}$  and  $P_5 = \{1,4\cdot 3\}$  are not. If  $P_1^* = \{P_1,P_2,P_3\}$  and  $P_2^* = \{P_2,P_4\}$ , then  $P_1^*$  is compatible with  $\langle L,t\rangle$  and  $P_2^*$  is not.

The next mappings are basic in the definition of our operators. As we saw in the example, the key is to settle a set of sets of positions for each literal, all them occupied by the same term. This one is done by the following mappings.

**Definition 3.** A mapping  $\Delta: Lit \to \mathcal{PPN}^+$  is called an assignment if there exists a term t such that, for every literal L,  $\Delta(L)$  is compatible with the pair  $\langle L, t \rangle$ .

Note that the term t does not have to be unique, for example, consider the identity assignment  $(\forall L \in Lit)[\Delta(L) = \{\emptyset\}]$ , the empty assignment  $(\forall L \in Lit)[\Delta(L) = \emptyset]$  or any mixture of both.

The assignments map a literal into a set of sets of positions. Each element of this set of positions will produce a literal, and the positions are the places where the new term is grafted. If  $\Delta: Lit \to \mathcal{PPN}^+$  is an assignment of positions and s is a term, we will denote by  $L\{\Delta(L)/s\}$  the set of literals, one for each element  $P \in \Delta(L)$ , obtained by grafting s in L at P. Formally

$$L\{\Delta(L)/s\} = \{L[P \leftarrow s] \mid P \in \Delta(L)\}\$$

For example, if L = sum(s(x), 0, s(x)), z is a variable,  $P_1^*$  is taken from the above example and  $\Delta$  is an assignment such that  $\Delta(L) = P_1^*$  then

$$\begin{split} L\{\Delta(L)/z\} &= \{L[P \leftarrow z] \,|\, P \in \Delta(L)\} \\ &= \{L[P \leftarrow z] \,|\, P \in P_1^*\} \\ &= \{L[P_1 \leftarrow z]\}, L[P_2 \leftarrow z], L[P_3 \leftarrow z]\} \\ &= \{sum(z, 0, s(x)), sum(s(x), 0, s(x)), sum(z, 0, z)\} \end{split}$$

We can now define our Learning Operators under Subsumption.

**Definition 4.** Let  $\Delta$  be an assignment and x a variable. We say that the mapping

is a Learning Operator under Subsumption (LOS) if for all literal L, if  $\Delta(L) \neq \emptyset$  then  $x \notin Var(L)$ .

Turning back to a previous example, if  $C = \{L_1, L_2, L_3\}$ , with  $L_1 = num(s(x))$ ,  $L_2 = less\_than(0, s(x))$ ,  $L_3 = less\_than(s(x), s(s(x)))$ , and the assignment

$$\Delta(L) = \begin{cases} P_1^* = \{ \emptyset, \{1\} \} & \text{if } L = L_1 \\ P_2^* = \emptyset & \text{if } L = L_2 \\ P_3^* = \{ \{1, 2 \cdot 1\}, \{1\} \} & \text{if } L = L_3 \\ \emptyset & \text{otherwise} \end{cases}$$

and considering the variable z as the variable to be grafted, then

$$C\{\Delta/z\} = \{num(s(x)), num(z), less\_than(z, s(z)), less\_than(z, s(s(x)))\}$$

These operators allow us to generalize a given clause and go up in the subsumption order on clauses as we see in the next theorem.

**Theorem 1.** Let C be a clause and  $\{\Delta/x\}$  a LOS. Then  $C\{\Delta/x\} \succeq C$ .

As we pointed above, the LOS define an operational definition of the subsumption relation. The last result states one way of the implication. The next theorem claims that all the learning processes based on subsumption of clauses can be carried out only by applying LOS.

**Theorem 2.** Let  $C_1$  and  $C_2$  be two clauses such that  $C_1 \succeq C_2$ . Then there exists a finite sequence (a chain)  $\{\Delta_1/x_1\}, \ldots, \{\Delta_n/x_n\}$  of LOS such that

$$C_1 = C_2\{\Delta_1/x_1\}\dots\{\Delta_n/x_n\}$$

For example, if we consider  $C_1 = \{p(x_1, x_2)\}$  and  $C_2 = \{p(x_2, f(x_1)), p(x_1, a)\}$  and the substitution  $\theta = \{x_1/x_2, x_2/f(x_1)\}$ . Then  $C_1\theta \subseteq C_2$  holds and therefore  $C_1 \succeq C_2$ . Decomposing  $\theta$  we can get  $\sigma_1 = \{x_2/x_3\}$ ,  $\sigma_2 = \{x_1/x_2\}$ ,  $\sigma_3 = \{x_3/f(x_1)\}$  and  $C_1\sigma_1\sigma_2\sigma_3 \subseteq C_2$  holds. Hence, considering the assignments

$$\Delta_1(p(x_2, f(x_1)) = \{\{2\}\} \text{ and } \Delta_1(L) = \emptyset \text{ if } L \neq p(x_2, f(x_1)) 
\Delta_2(p(x_2, x_3)) = \{\{1\}\} \text{ and } \Delta_2(L) = \emptyset \text{ if } L \neq p(x_2, x_3) 
\Delta_3(p(x_1, x_3)) = \{\{2\}\} \text{ and } \Delta_3(L) = \emptyset \text{ if } L \neq p(x_1, x_3)$$

we have  $C_1 = C_2\{\Delta_1/x_3\}\{\Delta_2/x_1\}\{\Delta_3/x_2\}$ . Note that if we consider the assignment  $\Delta(p(x_1, a)) = \{\{2\}\}$  and  $\Delta(L) = \emptyset$  if  $L \neq p(x_1, a)$ , then  $C_1 = C_2\{\Delta/x_2\}$  also holds.

### 4 A Quasi-Metric Based on Subsumption

The operational characterization of the subsumption relation given in the previous section gives us a natural way of formalizing the *closeness* among clauses. As we have seen, if  $C_1 \succeq C_2$  then there exists at least one chain of LOS from  $C_2$  to  $C_1$  and we can consider the length of the shortest chain from  $C_2$  to  $C_1$ .

**Definition 5.** A chain of LOS of length n from the clause  $C_2$  to the clause  $C_1$  is a finite sequence of n LOS  $\{\Delta_1/x_1\}, \{\Delta_2/x_2\}, \ldots, \{\Delta_n/x_n\}$  such that

$$C_1 = C_2 \{ \Delta_1/x_1 \} \{ \Delta_2/x_2 \} \dots \{ \Delta_n/x_n \}$$

If  $C_1 = C_2$ , we will consider that the empty chain, of length zero, maps  $C_2$  into  $C_1$ . The set of all the chains from  $C_2$  to  $C_1$  will be denoted by  $\mathbf{L}(C_2, C_1)$  and  $|\mathcal{C}|$  will denote the length of the chain  $\mathcal{C}$ .

Following the geometric intuition, if we consider these chains as *paths* from  $C_2$  to  $C_1$ , we formalize the *closeness* between clauses as the shortest path  $C_2$  to  $C_1$ . If  $C_1$  does not subsume  $C_2$ , we will think that  $C_1$  cannot be reached from  $C_2$  by applying LOS, so both clauses are separated by an infinite distance.

**Definition 6.** We define the mapping  $dc : \mathbb{C} \times \mathbb{C} \to [0, +\infty]$  as follows:

$$dc(C_2, C_1) = \begin{cases} min\{|\mathcal{C}| : \mathcal{C} \in \mathbf{L}(C_2, C_1)\} & \text{if } C_1 \succeq C_2 \\ +\infty & \text{otherwise} \end{cases}$$

The subsumption relation is not symmetric, so the mapping dc is not either. Instead of being a drawback, this property gives an algebraic characterization of the subsumption relation, since for any two clauses,  $C_1 \succeq C_2$  iff  $dc(C_2, C_1) \neq +\infty$ .

**Definition 7.** A quasi-metric on a set X is a mapping d from  $X \times X$  to the non-negative reals (possibly including  $+\infty$ ) satisfying:

 $\begin{aligned} &- & \left( \forall x \in X \right) d(x,x) = 0 \\ &- & \left( \forall x,y,z \in X \right) d(x,z) \leq d(x,y) + d(y,z) \\ &- & \left( \forall x,y \in X \right) \left[ d(x,y) = d(y,x) = 0 \Rightarrow x = y \right] \end{aligned}$ 

Notice that a quasi-metric satisfies the conditions to be a metric, except for the condition of symmetry. The next result states the computability of dc and provides an algorithm to compute it.

**Theorem 3.** dc is a computable quasi-metric.

*Proof (Outline)*. Proving that dc is a quasi-metric is straightforward from the definition. The proof of the computability is split in several steps. Firstly, for each substitution  $\theta$  we define the set of the splittings up:

$$Split(\theta) = \left\{ \sigma_1 \dots \sigma_n : \begin{array}{l} \sigma_i = \{x_i/t_i\} & x_i \notin Var(t_i) \\ (\forall z \in Dom(\theta))[z\theta = z\sigma_1 \dots \sigma_n] \end{array} \right\}$$

with  $length(\sigma_1 \dots \sigma_n) = n$  and  $weight(\theta) = min\{length(\Sigma) | \Sigma \in Split(\theta)\}$ . The next equivalence holds

$$dc(C_2, C_1) = \begin{cases} 0 & \text{if } C_1 = C_2 \\ 1 & \text{if } C_1 \neq C_2 \text{ and } C_1 \subseteq C_2 \\ \min\{weight(\theta) \mid C_1\theta \subseteq C_2\} & \text{if } C_1 \succeq C_2 \text{ and } C_1 \not\subseteq C_2 \\ +\infty & \text{if } C_1 \not\succeq C_2 \end{cases}$$

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Input: A non-empty substitution \theta
Output: An element of Split(\theta)
Set \theta_0 = \theta and U_0 = Dom(\theta) \cup Ran(\theta)
Step 1:
       If \theta_i is the empty substitution
             Then stop
             Otherwise: Consider \theta_i = \{x_1/t_1, \dots, x_n/t_n\} and go to Step 2.
Step 2:
       If there exists x_j \in Dom(\theta_i) such that x_j \not\in Ran(\theta_i)
             Then for all k \in \{1, \dots, j-1, j+1, \dots, n\} let t_k^* be a term
      such that t^k = t_k^* \{x_j/t_j\} Set \theta_{i+1} = \{x_1/t_1^*, \dots, x_{j-1}/t_{j-1}^*, x_{j+1}/t_{j+1}^*, \dots, x_n/t_n^*\} \sigma_{i+1} = \{x_j/t_j\} U_{i+1} = U_i
             set i to i+1 and go to Step 1.
             Otherwise: Go to Step 3.
Step 3:
       In this case let z_i be a variable which does not belong to U_i and set
       U_{i+1} = U_i \cup \{z_i\}
choose j \in \{1, ..., n\} y let T be a subterm of t_j such that T is not a variable
belonging to U_{i+1}. Then, for all k \in \{1, ..., n\} let t_k^* be a term
             such that t^k = t_k^* \{ z/T \}. Set
       \theta_{i+1} = \{x_1/t_1^*, \dots, x_n/t_n^*\}
       \sigma_{i+1} = \{z/T\}
set i to i+1 and go to Step 1.
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**Fig. 2.** The algorithm to compute the subset of  $Split(\theta)$ 

We can decide if  $C_1 \succeq C_2$  and, if it holds, we can get the finite set of all  $\theta$  such that  $C_1\theta \subseteq C_2$ , so to conclude the theorem we have to give an algorithm which computes  $weight(\theta)$  for each  $\theta$ . The Fig. 2 shows a non-deterministic algorithm which

generates elements of  $Split(\theta)$ . We prove that the algorithm finishes and for all  $\Sigma \in Split(\theta)$  the algorithm outputs a  $\Sigma^*$  verifying  $length(\Sigma^*) \leq length(\Sigma)$ .

The previous theorem provides a method for computing dc, but deciding whether two clauses are related by subsumption is an NP-complete problem [1], so, from a practical point of view we need a quick estimation of the quasi-metric before deciding the subsumption. The next result settles an upper and lower bounds for the quasi-metric under the assumption of subsumption.

**Theorem 4.** Let  $C_1$  and  $C_2$  be two clauses such that  $C_1 \not\subseteq C_2$ . If  $C_1 \succeq C_2$  then

$$|Var(C_1) - Var(C_2)| \le dc(C_2, C_1) \le min\{2 \cdot |Var(C_1)|, |Var(C_1)| + |Var(C_2)|\}$$

Proof (Outline). For each  $\theta$  such that  $C_1\theta \subseteq C_2$ ,  $\theta$  has at least  $|Var(C_1) - Var(C_2)|$  bindings and we need at least one LOS for each binding, hence the first inequality holds. For the second one, if  $C_1\theta \subseteq C_2$  then we can find n substitutions  $\sigma_1, \ldots, \sigma_n$  with  $\sigma_1 = \{x_i/t_i\}$  and  $x_i \notin Var(t_i)$  such that  $C_1\sigma_1 \ldots \sigma_2 \subseteq C_2$  verifying  $n = |\theta| + |Ran(\theta) \cap Dom(\theta)|$ . The inequality holds since  $Ran(\theta) \subseteq Var(C_2)$ ,  $Dom(\theta) \subseteq Var(C_1)$  and  $|\theta| \leq Var(C_1)$ .

If 
$$C_1 = \{p(x_1, x_2)\}$$
,  $C_2 = \{p(a, b)\}$  and  $C_3 = \{p(f(x_1, x_2), f(x_2, x_1))\}$  then 
$$dc(C_2, C_1) = |Var(C_1) - Var(C_2)| = 2$$
$$dc(C_3, C_1) = min\{2 \cdot |Var(C_1)|, |Var(C_1)| + |Var(C_2)|\} = 4$$

The above examples show that these bounds cannot be improved.

### 5 Related Work

The problem of quantifying the closeness among clauses has already been studied previously by offering distinct alternatives of solution to the problem. In the literature, a metric is firstly defined on the set of literals and then, the Hausdorff metric is used to get, from this metric, a metric on the set of clauses. This approach has two drawbacks. On the one hand, the Hausdorff metric exclusively depends on the extreme points, on the other, these literals are considered isolated: the possible relations among the literals of the same clause are not considered. Next we will see an example.

In [6], Nienhuys-Cheng defines a distance for ground atoms

$$-d_{nc,g}(e,e) = 0 -p/n \neq q/m \Rightarrow d_{nc,g}(p(s_1, \dots, s_n), q(t_1, \dots, t_m)) = 1 -d_{nc,g}(p(s_1, \dots, s_n), p(t_1, \dots, t_n)) = \frac{1}{2n} \sum_{i=1}^n d_{nc,g}(s_i, t_i)$$

and then, she uses the Hausdorff metric to define a metric on sets of ground atoms

$$d_h(A, B) = \max \left\{ \max_{a \in A} \{ \min_{b \in B} \{ d_{nc,g}(a, b) \} \}, \max_{b \in B} \{ \min_{a \in A} \{ d_{nc,g}(a, b) \} \} \right\}$$

The aim of this distance was to define a distance between Herbrand interpretations, so  $d_{nc,g}$  was only defined on ground atoms. In [8], Ramon and Bruynooghe extended it to handle non–ground expressions:

- $-d_{nc}(e_1, e_2) = d_{nc,g}(e_1, e_2)$  if  $e_1, e_2$  are ground expressions  $-d_{nc}(p(s_1, ..., s_n), X) = d_{nc}(X, p(s_1, ..., s_n)) = 1$  with X a variable.
- $-d_{nc}(X,Y) = 1$  and  $d_{nc}(X,X) = 0$  for all  $X \neq Y$  with X and Y variables.

This metric can be easily extended to literals: If A and B are atoms, we consider  $d_{nc}(\neg A, B) = d_{nc}(A, \neg B) = 0$  and  $d_{nc}(\neg A, \neg B) = d_{nc}(A, B)$ . By applying the Hausdorff metric to  $d_{nc}$  we have a metric  $d_h$  on clauses. We have implemented dc and  $d_h$  with Prolog programs. The following example allows us to compare this metric with our quasi-metric.

For all  $n \geq 0$ , consider the clauses

$$\begin{array}{ll} C_n \equiv sum(s^{n+1}(x_1), s^n(y_1), s^{n+1}(z_1)) & \leftarrow sum(s^n(x_1), s^n(y_1), s^n(z_1)) \\ D_n \equiv sum(s^{2n+1}(x_2), s^{2n}(y_2), s^{2n+1}(z_2)) \leftarrow sum(s^{2n}(x_2), s^{2n}(y_2), s^{2n}(z_2)) \end{array}$$

and the substitution  $\theta_n = \{x_1/s^n(x_2), y_1/s^n(y_2), x_3/s^n(y_3)\}$ . Then  $C_n\theta_n = D_n$  for all n and hence,  $C_n \succeq D_n$ . The next table shows the values of the quasi-metric  $dc(C_n, D_n)$  and the metric of Hausdorff  $d_h(C_n, D_n)$  for several values of N as well as the time of computation on a Pentium III 800 Mhz. in an implementation for SWI-Prolog 4.0.11.

N	$dc(C_n, D_n)$		$d_h(C_n,D_n)$	
	Seg	Q-dist	Seg	Dist
64	0.02	3	0.11	$\sim 2.7  10^{-20}$
128	0.06	3	0.21	$\sim 1.4  10^{-39}$
256	0.1	3	0.43	$\sim 4.3  10^{-78}$
512	0.26	3	0.93	$\sim 3.7  10^{-155}$
1024	0.67	3	2.03	$\sim 2.7  10^{-309}$

It can be easily calculated that, for all  $n \geq 0$ ,  $dc(C_n, D_n) = 3$ . If we use the Hausdorff metric  $d_h$  based on  $d_{nc}$  we have that, for all  $n \geq 0$ 

$$d_h(C_n, D_n) = \frac{1}{2^{n+1}}$$

which tends to zero in spite of the subsumption relation holds for all n.

In the literature, it can be found other formalizations of the closeness among clauses (e.g. [3] or [8]), but in all them there exists a strong dependence on the distance between individual elements.

### 6 Conclusions and Future Work

In the nineties, the success reached in real-life problems by learning systems based on clausal representation encouraged the development of techniques of

generalization, most of them designed ad hoc for a specific problem. The operators presented in this paper<sup>1</sup> might be a significant improvement in the field. The operators are not related to any specific system, they can be easily implemented and used in any system. But the main property is that the LOS are sufficient for all generalization process of clauses based on subsumption. As we have proved, the LOS are a *complete* set of generalization operators: If  $C_1$  subsumes  $C_2$  then  $C_1$  can be reached from  $C_2$  by solely applying LOS.

In the second part of the paper we define a quasi-metric on the set of clauses and give an algorithm to compute it and a method for a quick estimation. The process of quantifying qualitative relations (as subsumption) is a hard and exiting problem which arises in many fields of Computer Science (see [5]) which is far from a complete solution. We present a contribution to its study by defining a quasi-metric on the set of clauses in a natural way, as the minimum number of operators which map a clause into another. As we have seen, this quasi-metric considers the clauses as members of a net of relations via subsumption and overcomes the drawbacks found in others formalizations of closeness.

Finally the definition of quasi-metric is completed with an algorithm to compute it and a bound for a quick estimation. This estimation can be a useful tool for the design of new learning algorithms based on subsumption.

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<sup>&</sup>lt;sup>1</sup> A preliminary version of these operators appeared in [2].

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