Learning to Transfer Knowledge Between Reference Systems

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Abstract

Representation and inference of spatial knowledge play a fundamental role in spatial reasoning, which itself is an important component of many applications such as Geographic Information Systems or robotics. This paper discusses how an existing relation between speaker-relative and absolute spatial reference systems can be automatically learned by an inductive relational machine learning system.

Introduction

There has been extensive empirical research into cognitive linguistics exploring different reference systems which are used to describe spatial situations across different cultures (Levinson 1996)(Pederson 1993). The research described in this paper focuses on two reference systems which are known as speaker-relative and absolute. The left-right system and the cardinal directions respectively, are typical examples of these. In (Pederson 1993) it is suggested that the speaker-relative and the absolute reference systems seem to be interchangeable, meaning that relations established or learned in one of these reference systems could be transferred to the other and used for reference and/or spatial reasoning. This assumption motivated Brennan and Wilson (Brennan and Wilson 1999) to further investigate the characteristics of both speaker-relative and absolute reference systems and to propose a logic formalism that represents the interchangeability between them. The fact that the proposed logic formalism is represented as first-order logic expressions suggests learning these expressions using a machine learning techniques.

This paper discusses the results obtained when investigating the feasibility of learning the interchangeability between reference systems automatically and compares the results with the formal approach proposed in (Brennan and Wilson 1999). In order to accomplish this, the paper is organised as follows: Section 2 introduces the main ideas about relational and absolute reference systems in order to subsidise the

presentation of the formalism proposed by Brennan and Wilson. Section 3 introduces the main concepts of the machine learning system FOIL in order to establish the basic terminology. We then present and discuss the results of the experiments showing how this system learns to express relations in an absolute system in terms of relations in a speaker-relative system. In Section 4 we compare the results with the proposed formal description and finally, in Section 5 we present our conclusions.

Formalising the Relationship Between Speaker-Relative and Absolute Systems

According to Levinson (Levinson 1997), spatial systems can be categorised into coordinate or non-coordinate systems. We would like to differentiate between two of the coordinate spatial systems - the speaker-relative system and the absolute reference system. The former embodies extended body regions or regions intrinsic to an object (which are considered to be the "natural" sub-division of space). The latter is characterised as a system that, apparently (in a perceivable time) does not change spatially. When a reference object (RO) is placed in a static environment, the spatial relation between the RO and any other object changes when the position of the RO changes, irrespective of which of the two reference systems is used. It should not be forgotten that in the speaker-relative reference system the spatial relation also changes with the change of the so called perspective.

Pederson (Pederson 1993) discusses the linguistic and conceptual contrasts between speaker-relative and absolute reference systems using, as an example, the urban and rural Tamil speakers. Urban Tamil speakers use the cardinal system (i.e. the absolute system North – South – East – West) exclusively for describing large-scale space and the left/right system to describe manipulable spaces (i.e. table-top spaces) while rural Tamil speakers use the cardinal system with both large-scale and table-top spaces. Psychological evidence suggests there are natural spatial categories such as the relative orientation relations (i.e. speaker-relative reference system) mentioned above.

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However, the fact that some cultures such as the rural Tamil and many Aboriginal tribes use absolute system relations to describe both manipulable and large-scale spaces, gives rise to the assumption that there are natural spatial categories underlying both the absolute and speaker-relative reference systems. Therefore, it should be possible to learn those relations.

The work described in (Brennan and Wilson 1999) is based on a spatial model described in (Hérnandez 1994) where a qualitative representation of positional information is proposed. According to this model the spatial relations are divided into two classes - orientation and topological relation. For the orientation relation, the space around each object is sub-divided into eight subspaces. These eight sub-spaces can be approached as four main spaces: front, back, right and left and four secondary spaces which are the results of the overlap of two neighbouring main spaces, namely front-right, front-left, back-right and back-left. Topological relations are then added to each sub-space to describe the boundaries of the direct neighbours (i.e. if they overlap, touch or do not touch each other). The two classes of relations can be used to discuss the position of a reference object (e.g. a robot moving through space) with respect to other objects in the same scene.

For learning of the spatial relations discussed in this paper, we will assume there are four objects, each of them placed in one of the main spaces. These are the objects to be localised (LO) and are described by their natural language description (e.g. a chair is described as such by the name "chair"). The reference object (RO) is a "person" referred to as a learner with an inherent front. The learner is placed in one position within a static object constellation (ie. the way objects are positioned in relation to each other). For each position the learner will rotate on its principal axis (i.e. the bottom-top-axis) in 90° steps (this is only a cognitive estimate). In this paper, the values a, al, all, or alll represent the learner in the same position, performing 90° clockwise turns on his/her own bottom-top axis as shown in Figure 1.

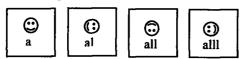


Figure 1. Identifying four different perspectives of the learner

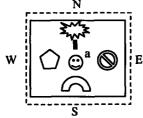


Figure 2. The learner a placed in a scene

The learner will be positioned in the centre of the static object constellation as shown in Figure 2.

The learner's relation to each of the LO's in this constellation is determined by an intrinsic reference frame considering the inherent front of the RO. In the case of the speaker-relative reference system, four perspectives are taken into account for the specified position. This means that for this position, four different speaker-relative relations between the learner and each LO can be determined. Secondary spaces will not be discussed in this paper because they can be induced in exactly the same way as the primary spaces.

We now briefly present a formal description of the relations between the speaker-relative and the absolute reference systems, as described in (Brennan and Wilson 1999). The description uses the following notation:

```
Y
                  reference object ("person") - RO
                  object x<sub>i</sub> to be located - LO
ΧĮ
                  relations in the speaker-relative system:
ſΤ
                     left(l), right(r), back(b), front(f)
ra
R_r(x_k,y,rr,p_j)
                  relations in the absolute system:
R_a(x_k,y,ra)
                     North(N), South(S), East(E), West(W)
                  xk and y satisfy the relative relation rr,
                     considering perspective pi
                  x<sub>k</sub> and y satisfy the absolute
                     relation ra
```

and the clockwise rotation is implemented by the function perspective defined as:

```
perspective(1)=rotation(0°)
perspective(j)=perspective(j-1)+rotation(90°) j=2,3,4
```

The relations in the absolute reference system, ie., South, West, North and East can be defined in terms of the relations in the speaker-relative reference system i.e., front, back, right and left by the next four logical expressions, respectively, where p_j (j=1,2,3,4) stands for perspective(j).

```
 \forall x_i \forall y [R_a(x_i,y,S) \leftrightarrow R_r(x_i,y,f,p_1) \land R_r(x_i,y,l,p_2) \\ \qquad \land R_r(x_i,y,b,p_3) \land R_r(x_i,y,r,p_4)] \quad (1) \\ \forall x_i \forall y [R_a(x_i,y,W) \leftrightarrow R_r(x_i,y,r,p_1) \land R_r(x_i,y,f,p_2) \\ \qquad \land R_r(x_i,y,l,p_3) \land R_r(x_i,y,b,p_4)] \quad (2) \\ \forall x_i \forall y [R_a(x_i,y,N) \leftrightarrow R_r(x_i,y,b,p_1) \land R_r(x_i,y,r,p_2) \\ \qquad \land R_r(x_i,y,f,p_3) \land R_r(x_i,y,l,p_4)] \quad (3) \\ \forall x_i \forall y [R_a(x_i,y,E) \leftrightarrow R_r(x_i,y,l,p_1) \land R_r(x_i,y,b,p_2) \\ \qquad \land R_r(x_i,y,r,p_3) \land R_r(x_i,y,f,p_4)] \quad (4)
```

The following section investigates how relations between two reference systems can be automatically learned and how the results of the learning process relate to the above formal expressions.

Learning to Transfer Spatial Knowledge

FOIL (Cameron-Jones and Quinlan 1994) is a system for inducing function-free relational Horn clause definitions from examples (ground facts) of the target relation and extensionally defined relations (i.e. relations defined as ground facts). It learns the target relation in terms of the target and other given relations (known as background knowledge). The learning process in FOIL happens from the general to the specific, i.e. in a top-down approach. Given the positive and negative tuples that define the target relation and the positive tuples that define the background relations FOIL's task is to learn a functionfree Horn clause definition of the target relation using the given knowledge. The user can specify all the positive tuples and leave FOIL to generate the negative tuples using the Closed World Assumption (CWA). To have a quick grasp of the way FOIL operates, consider the problem of learning an expression for the relation path/2 (meaning that the predicate path has arity 2) using as background knowledge the relation linked/2. The expression for path/2 is true if there is a path between any two nodes in a graph and false otherwise. The graph shown in Figure 3 can be used as a source for the extensionally defined relations to instruct the system. Table 1 describes the facts that are pictorially represented in Figure 3.

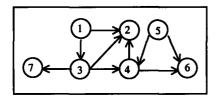


Figure 3. A graph defined by 7 nodes and 9 edges

Table 1. Background knowledge and positive examples of relation path/2 extracted from Figure 3

Background Knowledge		Positive Examples	
linked(1,2).	linked(4,2).	path(1,2).	path(3,6).
linked(1,3).	linked(4,6).	path(1,3).	path(3,7).
linked(3,2).	linked(5,4).	path(1,4).	path(4,2).
linked(3,4).	linked(5,6).	path(1,6).	path(4,6).
linked(3,7).		path(1,7).	path(5,2).
		path(3,2).	path(5,4).
		path(3,4).	path(5,6).

Given the knowledge described in Table 1, FOIL induces a general definition of the relation path/2 given by the two clauses:

path(A,B) := linked(A,B).path(A,B) := linked(C,B), path(A,C).

In the application described next, FOIL is adopted as the learning procedure used by a learner in order to automatically acquire general spatial knowledge from specific examples. With this in mind, FOIL and the learner will be considered as the same "entity". In order to explore the learning of relations between a relative and an absolute reference system, we consider the scene shown in Figure 2, which can be approached from either reference system. Note that the four different cardinal directions were arbitrarily chosen - whatever this choice is, the learning procedure will be the same but, obviously, the resulting expressions will differ accordingly. In the discussion that follows we focus on learning the absolute relation north_of/2 in terms of the primitive relation clockwise/2 and the speaker-relative relations right/2, left/2, front/2 and back/2. The learning of the other absolute relations, namely east of/2, south of/2 and west of /2 can be conducted in a similar way. The speaker-relative system as pictured in Figure 2 can be described by the facts stated in Table 2 which, together with the facts described in Table 3, are assumed as background knowledge for the learning process. However, using only these facts as background knowledge and the four positive examples of the relation north_of extracted from Figure 2 (see Table 4) is not sufficient for the learner to induce a general clause that expresses north_of in terms of the relative relations. For this reason, ten situations like the one shown in Figure 2 were used in the experiments we conducted. This resulted in a background knowledge with 160 facts and a set of 40 positive examples of the relation north_of.

Table 2. Facts describing the four relations representing the speaker-relative reference system in Figure 2

back(tree,a). back(bridge,all). front(bridge,a). front(tree,all). right(shed,a). right(signal,all). left(signal,a). left(shed,all). back(signal,al). back(shed,alll). front(shed.al). front(signal.alll). right(tree,al). right(bridge,alll). left(bridge.al). left(tree,alll).

Table 3. Two primitive relations (part of the background knowledge)

initial_perspective(a). clockwise(a,al). clockwise(al,all). clockwise(all,alll). clockwise(alll,a).

Conducting a thorough analysis it can be observed that it is also necessary to establish the initial perspective defined by the learner, in order to be able to establish the relations between both reference systems. This is obvious as, to orient ourselves in the environment, we need landmarks of some kind (objects which do not shift in a perceivable time for the purpose of orientation; in our case one object in the scene is chosen as the initial landmark). Therefore, the relation *initial_perspective* is assumed to be

well-known by the learner i.e., the learner based on his/her knowledge of the scene, is capable of discriminating the perspective which makes this predicate true (as shown in Table 3).

As previously mentioned, there are four possible initial perspectives the learner can occupy in the scene, namely, a, al, all and alll. Depending on this value (given by the predicate initial_perspective) the learner induces four different sets of rules. Table 4 shows all four sets of rules, each corresponding to one particular value of initial_perspective and Figure 5 shows the diagrams corresponding to the first set of clauses in Table 5.

Table 4. Positive examples of the relation *north_of* extracted from Figure 2

north_of(tree,a). north_of(tree,al). north_of(tree,all). north_of(tree,all).

Table 5. Inducing the relation *north_of* considering possible initial perspectives of the learner

		ssible linual perspectives of the learner		
initial_	#	Induced Relations		
perspectiv				
e				
a,b,	1	north_of(A,B):- not(initial_perspective(B)),		
c,d,		front(A,B), clockwise(B,C),		
e,f,		clockwise(D,B),		
g,h,	\	not(initial_perspective(C)),		
i,j		not(initial_perspective(D)).		
-0	2	north_of(A,B):- initial_perspective(B),		
1	~	back(A,B).		
l	3	north_of(A,B):- right(A,B), clockwise(C,B),		
		initial_perspective(C).		
1	4			
ļ .	4	north_of(A,B):- clockwise(B,C),		
1	1	clockwise(D,B),		
		initial_perspective(C),		
	<u> </u>	front(A,D).		
al,bl,	5	north_of(A,B):-front(A,B),		
cl,dl,		clockwise(C,B),		
el,fl,	ł	initial_perspective(C).		
gl,hl,	6	north_of(A,B):- back(A,B),		
il,jl		clockwise(B,C),		
		initial_perspective(C).		
	7	north_of(A,B):- initial_perspective(B),		
1	1	right(A,B).		
l	8	north_of(A,B):- not(initial_perspective(B)),		
	j	clockwise(B,C),		
i	f	clockwise(D,B),front(A,D),		
Ī	1	not(initial_perspective(C)),		
]		not(initial_perspective(D)).		
all,bll,	9	north_of(A,B):- initial_perspective(B),		
cll,dll,	S	front(A,B).		
ell,fll,	10	north_of(A,B):- not(initial_perspective(B)),		
gll,hll,		back(A,B), clockwise(B,C),		
ill,jll	1	clockwise(D,B),		
}]	not(initial_perspective(C)),		
	i	not(initial_perspective(D)).		
	11	north_of(A,B):- right(A,B),		
1		clockwise(B.C),		
	ĺ	initial_perspective(C).		
	12	north_of(A,B):- clockwise(C,B),		
		initial_perspective(C),		
1	1	front(A,C).		
alll,blll,	13	north_of(A,B):-front(A,B),		
ain,viii,	13	norm_or(v,p),-norm(v,p),		

clll,dlll,		clockwise(B,C),
elll,flll,	ļ	initial_perspective(C).
glll,hlll,	14	north_of(A,B):- back(A,B),clockwise(C,B),
i111,j111		initial_perspective(C).
	15	north_of(A,B):- not(initial_perspective(B)),
ł	1	clockwise(B,C),
		clockwise(D,B),front(A,C),
	ĺ	not(initial_perspective(C)),
	l	not(initial_perspective(D)).
	16	north_of(A,B):- clockwise(C,B),
1	ĺ	initial_perspective(B),
		front(A,C).

In Figure 4 the initial perspective is represented by a white smiley face and any other perspective by a dark smiley face. This diagram attempts to capture the functional aspects of the first set of four clauses shown in Table 5. When analysing Figure 4 it is important to always have in mind that, within each of its divisions, the various "smiley faces" (black or white) represent the perspectives of one unique learner. In Figure 4 the notation Variable—instantiation_of_Variable (e.g C-all) is adopted in order to promote comprehension. For these diagrams, variable A is instantiated with the atom tree.

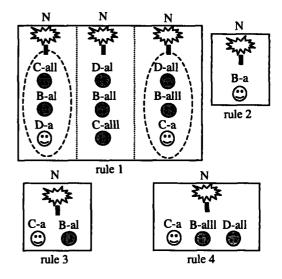


Figure 4. Diagrams corresponding to rules 1-4 from Table 5 (initial perspective a)

The diagram corresponding to rule 2 is straightforward. In the diagram corresponding to rule 3, the initial perspective C is instantiated with a. The variable B is instantiated with al when proving clockwise(C,B); for these instantiations, right_of(tree,B) is true and, consequently, north_of(tree,B) is true. In the diagram corresponding to rule 4, the initial perspective C is instantiated with a; note that variable B is the first argument of clockwise(B,C) meaning that, in order to prove this predicate true, B should be instantiated with all. And further, when proving clockwise(D,B), D is instantiated with all. With these instantiations, front_of(tree,D) is proved true and consequently, so is

north_of(tree,B).

The rule 1 diagram in Figure 4 represents different possibilities that arise from the negated literal. The two dotted ellipses identify the learner's perspectives that will make the interrogation north_of(A,B) fail. The situation the first ellipse fails identified by initial_perspective(D) for D instantiated with a is true and consequently, the negation fails (the same applies to the second, with variable C). So, when proving the interrogation: ?- north_of(tree, all). rule 1 will succeed only when fact front_of(tree,all) can be proved. For the other sets of clauses, similar diagrams can be created. If these sets of clauses are to be used to infer knowledge, as part of a knowledge base, some details should be considered, mainly due to negated literals that are part of four of the induced clauses (those identified as 1, 8, 10 and 15).

Formal Descriptions versus Induced Relations

As far as the formal descriptions presented in Section 3 and the results induced in Section 4 are concerned, the role of the function *perspective* is the same as that of the predicate *clockwise*. In this sense, the four different perspectives p_1 , p_2 , p_3 and p_4 correspond to the perspectives a, al, all and alll of the learner respectively. Both "transform" a certain perspective of the learner into another (by means of a 90° degrees clockwise rotation).

In the following discussion we focus on the logical expression (3) since we are referring to results concerning the relation *north_of* presented in the previous section. Each of the predicates R_r can be associated with a set of four rules induced by FOIL. The knowledge represented by expression (3) was empirically learned as the set of 16 rules in Table 5. Considering the first group of four rules in Table 5, the learner generalised, based not only on the initial perspective (a) but also on the three other perspectives (al,all,alll), since they were part of the background knowledge. The same occurs for the other three sets of four rules.

Expression (3) can be associated with each of the sets shown in Table 5; and each of its predicates Rr can be associated with a particular rule. Considering the first set of four rules, the predicate $R_r(x_i,y,b,p_1)$ can be mapped directly onto rule 2, $R_r(x_i,y,r,p_2)$ onto rule 3 and $R_r(x_i,y,f,p_3)$ onto rule 4. However, $R_r(x_i,y,l,p_4)$ is not mapped directly onto rule 1 as would be expected. This is explained by the way FOIL conducts the heuristic search for selecting the literals that will appear in the body of a clause. "Relations are ordered first by arity, and then by the proportion of positive tuples in the tuple space. Four relations have the same arity, tuple space and proportion of positive tuples: front, back, right, left. FOIL cannot distinguish them and so the original order makes a difference" (Quinlan 1999).

Conclusions

Representation and inference of spatial knowledge play a fundamental role in spatial reasoning, which in itself is an important component of many applications such as Geographic Information Systems or robotics. This paper described the use of a machine learning system for inducing spatial relations. The learned spatial relations are represented as Horn clauses and can be used by a Prologlike interpreter for inferring new knowledge. The main contribution of the experiments described, however, was to show that the interchangeability between relative and absolute reference systems can be empirically learned. The results obtained confirm, to a certain degree, the formalisation of the relation between these reference systems as proposed in (Brennan and Wilson 1999). It is important to mention that the experiments were restricted by the fixed positioning of objects and by considering only four perspectives. This however could be extended. We believe the automatic learning of interchangeability between reference systems can be of help in spatial reasoning. Reasoning systems could learn new relations, which they may not know yet. This could help these systems through unknown or unfamiliar situations.

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