

Contrastive Characters of Spatial Composition Process between Architecturally Trained and Untrained Students

Noritoshi Sugiura¹ and Shigeyuki Okazaki¹

¹ Department of Architecture, Mukogawa Women's University, Nishinomiya, Japan

Corresponding author: Noritoshi Sugiura, Department of Architecture, Mukogawa Women's University, 1-13 Tozaki-cho, Nishinomiya, Hyogo, 663-8121, Japan, E-mail: sugiura@mukogawa-u.ac.jp

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Abstract: Inductive logic programming was applied to the analysis of spatial composition processes using an architectural space montage technique. The complexly structured data of the spatial composition processes that consist of many objects, their relationships, and their attributes were modeled with first-order logic. One architectural space montage technique experiment was conducted on 14 architecturally trained students and on 14 untrained students. These experimental cases were analyzed by Progol, which is one ILP system. 513 rules for the trained students and 458 for the untrained students were found. By comparing these rules, we found contrastive characteristics between the two groups from four points of view: (1) extension method of chain of miniatures, (2) relationship as basic unit of composition, (3) type of miniature, and (4) multiplicity of rules.

1. Introduction

In this study, the process of architectural design was analyzed by inductive logic programming (ILP) (Muggleton and Raedt, 1994; Lavrac and Dzeroski et al., 1999), which is a machine learning technique based on first-order logic that executes inductive reasoning and generalizes the results from examples to generate new concepts.

In various contexts, it has been reported in the domain of phenomenology or developmental psychology that humans have unconscious spatial schemata that enable them to recognize space (Merleau-Ponty, 1945; Piaget, 1963). In support of this theory, it has been proposed that the human design process is affected by such schemata that appear as the compositional patterns of such architectural elements as walls, furniture, buildings, and so on (Schulz, 1971; Bollnow, 1963). These spatial schemata and compositional patterns could be important factors to form culture. To create an architectural space suitable for human recognition, to re-interpret existing architectures and to understand culture, we must find the latent patterns of spatial composition affected by the spatial schemata from a psychological point of view. This is currently a key issue in the architectural field.

From the above context, this study investigates the patterns in the initial process of architectural design, which visualizes individual mental images. We previously focused on discovering the peculiar patterns of the architectural design process of architecturally trained and untrained individuals (Sugiura and Okazaki, 2002) and the relationship among their patterns and Japanese architecture and landscapes (Sugiura and Okazaki, 2011). This paper focuses on the contrastive characteristics between two groups.

Several studies on architectural design patterns have been done. For example, the Shape-Grammar was defined as a set of production rules that can generate floor plans in F. L. Wright's architectural style (Koning et al., 1981). The Shape-Grammar,

however, does not reflect the actual design process. In this paper, actual design processes using an architectural space montage technique (ASMT) were analyzed.

ASMT was developed by one of the authors to elucidate the fundamental patterns of spatial composition that exist in human beings. In an experiment using ASMT, participants composed architectural spaces by placing such miniatures as walls and furniture at a scale of 1:50 on a white board (Fig. 1). In this study, we regarded a spatial composition process using this method as an initial process of architectural design, which is the process of visualizing individual mental images.



Fig. 1. Examples of models constructed using ASMT by an undergraduate (left) and a kindergartener (right)

In one ASMT experiment, dozens to hundreds of miniatures can be placed. Moreover, a newly placed miniature has many relationships to the previously placed miniatures. It is difficult to discover patterns by only relying on human inspection in such complexly structured data as those in the spatial composition process. Therefore, in this study, we applied Progol, one ILP system, to identify the latent patterns of the spatial composition process in ASMT. ILP has been applied to various fields, including finding the patterns from spatial relational structures (e.g., graphic design of magazine (Chiba, 1999), room arrangements in a house (Mizoguchi, 1995), and molecular models (King, 1995)). However, there has been no study that tried to apply ILP to learning from such structures that include ordinal relationships as the spatial composition process.

In the rest of this paper, brief overviews of ASMT and Progol are given in Sections 2 and 3. In Section 4, the spatial composition process is modeled with the Entity-Relationship (ER) model and described with first-order logic. In Section 5, the spatial composition processes by architecturally trained and untrained students are analyzed. The results of ASMT experiments and rules discovered by Progol are shown. From these rules, contrastive characteristics are discussed between the two groups in Section 6. Finally, our conclusions and future work are stated in Section 7.

2. ASMT

ASMT was originally developed in the context of psychotherapy. Clinical psychological analysis has been undertaken on the characteristic patterns of the spatial compositions formed by schizophrenic patients, elementary school children, mentally handicapped children, and kindergarteners (Okazaki et al., 1992a, 1992b, 1997, 1999). In ASMT, since architectural space is composed by placing three-dimensional miniatures, participants are not limited by their drawing ability and can readily express a 3D architectural space. Moreover, we can clearly observe the steps in the design process.

The types of miniatures used in ASMT differ slightly depending on the experimental groups. In this study, we prepared the following 44 kinds of miniatures (Fig. 4): six kinds of styrene walls of different lengths (1800, 2700, 3600, and 5400 mm) and various colors (blue, red, yellow, green, white, gray, pink, ivory, cream, mint, and grain) with various openings, mirror walls and glass walls in lengths of 3600 and 5400 mm with the glass walls in various colors (blue, orange, and clear), columns, twelve kinds of furniture (e.g. table, sofa, carpet, shelf), six different sanitary fixtures (e.g., sink, toilet, bathtub), four different human figures, a dog and a cat, six types of vegetation (e.g., grass, conifers, broadleaf trees, hedges), and five different architectural elements (e.g., balcony, stairs). Fig. 2 shows examples of these miniatures.

In the experimental setting and procedure, a white board (60 by 90 cm) was placed horizontally on a desk in the experimental room. Two smaller white boards (45 by 30 cm) were placed on both sides of the larger board with miniature walls arranged on top of the boards. The other miniatures were displayed on a shelf.

Subjects constructed a model of their “dream” house on the large white board. The experiment ended when they informed the experimenter that they were finished. The state of the model in the experiment was constantly recorded by video camera.

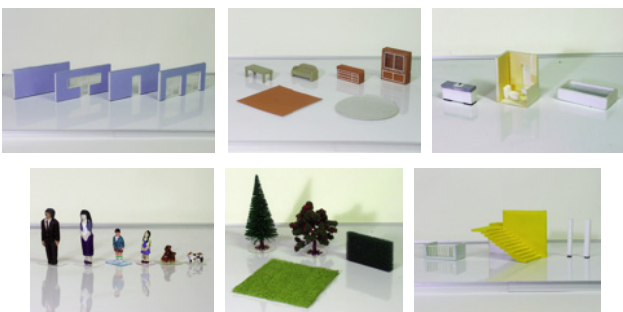


Fig. 2. Miniatures used in ASMT experiment: walls, furniture, sanitary fixtures, human and animal figures, vegetation, and architectural elements

3. ILP and Progol

Progol, which is one ILP system created by Muggleton (1995), combines Inverse Entailment with general-to-specific search through a refinement graph and allows arbitrary Prolog programs

as background knowledge and arbitrary definite clauses as examples. Input data to Progol consist of a set of positive examples $E+$, a set of negative examples $E-$, a set of background knowledge BK , and the mode declarations used by Progol to guide the process of constructing a generalization from examples. From these data, hypotheses are constructed as Horn clauses.

Hypothesis H is complete if $\forall e \in E+: BK \cup H \models e$, where “ \models ” means logical entailment. Hypothesis H is consistent if $\forall e \in E-: BK \cup H \not\models e$. Hypotheses can predict whether unknown examples belong to positive or negative examples.

In this paper, one version of Progol, P-Progol 2.7.5, was used. P-Progol was implemented by Srinivasan and Rui in Prolog based on the Progol algorithm (1999).

4. Modeling of Spatial Composition Process

To logically describe the design process, we defined a unit of the spatial composition process as miniature placement with relationships to the previously placed miniatures. The spatial composition process is a set of miniature placements.

4.1. DATA MODEL

The spatial composition data by ASMT are complexly structured and are collections of architectural objects with geometric relationships. The spatial composition process data were modeled with the ER model (Chen, 1976), a well-known semantic data model. An example of the representation of the spatial composition process using an ER data model is shown in Fig 3. A placed miniature corresponds to an entity. A geometric relationship occurs among the newly placed and existing objects. Each placed miniature has three attributes: type, the angle between the miniature and the white board’s long side, and the ordinal number of the placement occurrence. Each relationship has three attributes: the relation type, the connecting point, and the difference between the ordinal numbers attached to the objects. In addition, the IS-A hierarchies of the attributes based on the inclusion relation among concepts are known in advance (Figs. 4 and 5).

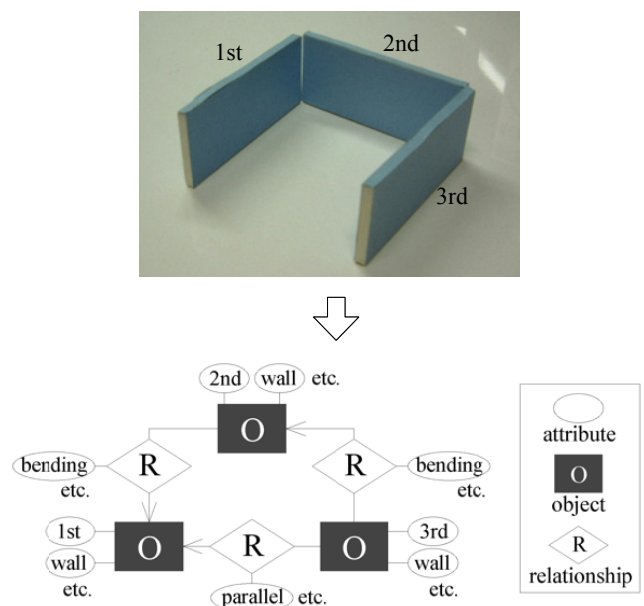


Fig. 3. Example of representation of spatial composition process using ER data model

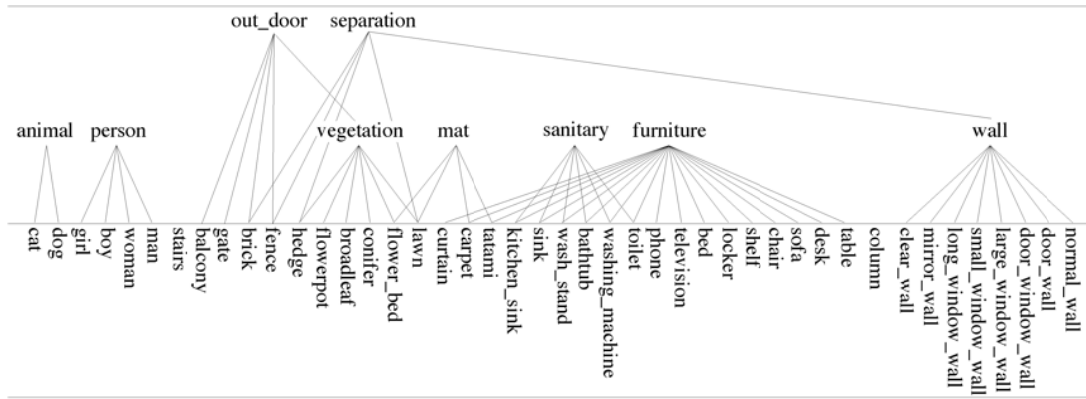


Fig. 4. Hierarchy of object types

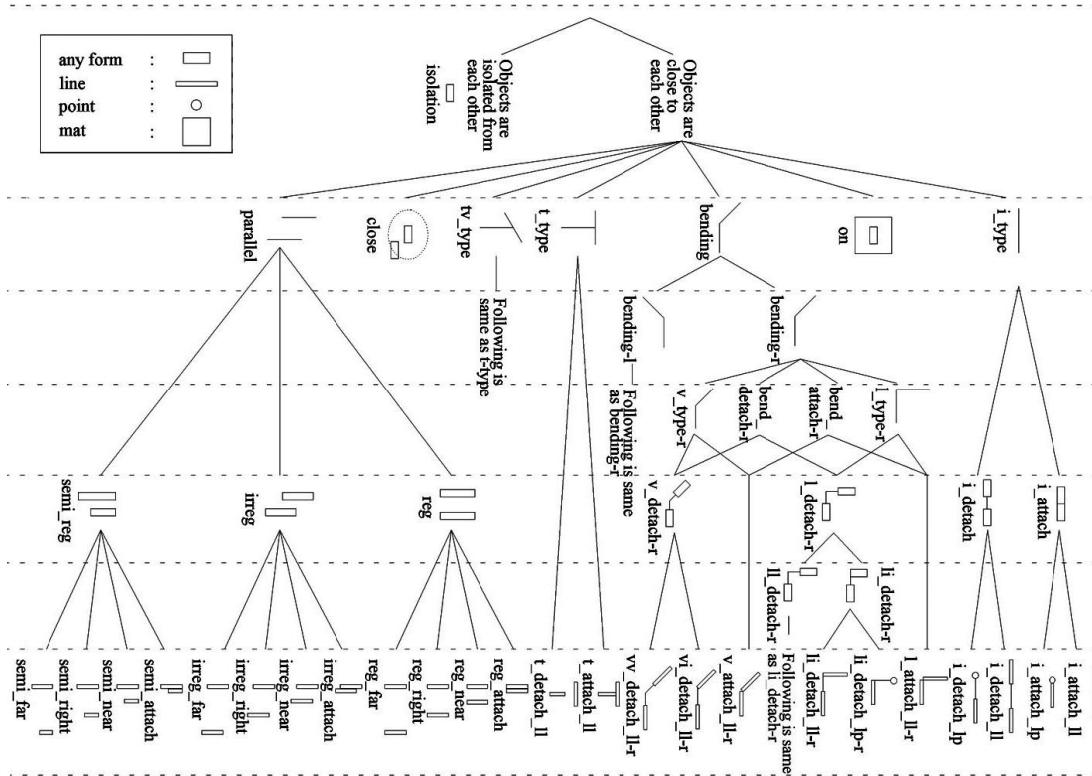


Fig. 5. Hierarchy of relation type

4.2. FIRST-ORDER REPRESENTATION

The spatial composition process modeled as an ER model is described as clauses in first-order logic. A predicate *placement* was defined for each placement, predicates *type* and *angle* were defined for each miniature, and a predicate *relation* was defined for each relationship. The information described with *placement* is used as an example, and the information described with *type*, *angle*, and *relation* is used as background knowledge. An example of the description is shown in Fig. 6.

5. Analysis

5.1. RESULTS OF ASMT EXPERIMENTS

One ASMT trial was individually conducted with 14 university students trained in architectural design and 14 untrained university students. The participants composed their “dream” house (Fig. 7).

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placement(1001).
placement(1002).
...
placement(1091).
placement(1092).

type(1001,lawn).
angle(1001,0).
relation(1001,isolation,none,no_dif,no_obj).
type(1002,lawn).
angle(1002,0).
relation(1002,close,none,1,1001).
...
type(1091,broadleaf).
relation(1091,li_detach_lp-1,top,32,1059).
relation(1091,li_detach_lp-1,top,31,1060).
type(1092,door_wall).
angle(1092,90).
relation(1092,li_detach_ll-1,top,42, 1050).
relation(1092,t2_touch,top,36,1056).
    
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Fig 6. Description of spatial composition process



Fig. 7. Results of ASMT experiments with architecturally trained (left) and untrained students (right): ID, participant ID, working time T (min.) of experiment, number of placements PN

5.2. LEARNING METHOD

Progol induced rules from the following two kinds of input data:

- (1) Placements by the trained students were set as positive examples and those by the untrained students were set as negative examples.
- (2) Placements by the untrained students were set as positive examples and those by the trained students were set as negative examples.

The rules induced from input data (1) and (2) indicate the characteristic patterns of the trained students and untrained students.

5.3. RESULTS OF PROGOL LEARNING

As a result, 513 and 458 rules were found from data (1) and (2). The rules, whose *Cov* and *CM* were more than 0.5% and 2/14, were regarded as common rules, where *Cov* means the coverage of the rule and *CM* is the number of members whose placements were set as positive examples and were covered by the rule. The numbers of common rules of the trained and untrained students were 30 and 28. The common rules of each group are shown in Tables 1 and 2.

6. Discussion

6.1. VALIDATION OF RULES

We measured the classification accuracy of unknown examples, which had not been used for Progol learning, using five-fold cross-validation (Weiss, 1990). The 28 experimental cases (Fig. 7) were split into five folds. Each fold contains cases by groups of the same number. The examples containing four folds were set as training examples from which Progol induced rules. The examples contained in the remaining fold were used for validation and classified as negative or positive using the induced rules. The above procedures were repeated five times while changing the combination of the folds. The predictive accuracy of positive examples PA^+ and negative examples PA^- was calculated by $PA^+ = TP/P$ and $PA^- = TN/N$, where TP is the number of correctly classified positive examples, TN is the number of correctly classified negative examples, P is the total number of positive examples for training, and N is the total number of negative examples for training. The average of PA^+ and PA^- was calculated by $F = 2P^+P^-/(P^+ + P^-)$. The predictive accuracies of the rules of the trained and untrained students were 0.510 and 0.541.

Table 1-1. Rules of trained students: IDs of rule *RID*, number of positive examples covered by rule *CE*, coverage of rule *Cov (%)*, number of members whose placements are covered by rule *CM*, description of rules, and diagram of rules

<i>RID</i>	<i>CE</i>	<i>Cov (%)</i>	<i>CM</i>	Description of rules	Diagram
<i>Rt1</i>	83	4.61	6/14	placement (A):-type (A, column).	
<i>Rt2</i>	23	1.28	4/14	placement (A):-type (A, separation), relation (A, vi_detach-r, root, B, C), relation (C, irreg, right, D, E).	
<i>Rt3</i>	23	1.28	7/14	placement (A):-type (A, separation), angle (A, 0), relation (A, li_detach-lp, none, B, C).	
<i>Rt4</i>	20	1.11	7/14	placement (A):-relation (A, i_attach, top, B, C), relation (C, irreg, right, D, E), relation (E, i_detach, top, F, G), type (G, wall).	
<i>Rt5</i>	20	1.11	2/14	placement (A):-angle (A, ambiguous), relation (A, irreg, right, B, C).	
<i>Rt6</i>	19	1.05	5/14	placement (A):-relation (A, irreg, left, B, C), type (C, wall), relation (C, irreg, left, 12, D).	
<i>Rt7</i>	18	1.00	4/14	placement (A):-type (A, person), relation (A, close, none, B, C), relation (C, close, none, D, E), type (E, vegetation), relation (E, isolation, none, F, G).	
<i>Rt8</i>	17	0.94	6/14	placement (A):-type (A, separation), relation (A, t_attach, root, B, C), type (C, separation), angle (C, 90).	
<i>Rt9</i>	16	0.89	8/14	placement (A):-type (A, furniture), relation (A, irreg, right, B, C), relation (C, i_detach, top, D, E), type (E, wall).	
<i>Rt10</i>	16	0.89	4/14	placement (A):-relation (A, irreg, left, B, C), type (C, wall), relation (C, bend_attach-l, root, 5, E), type (E, wall).	
<i>Rt11</i>	15	0.83	8/14	placement (A):-type (A, wall), relation (A, irreg, right, B, C), angle (C, 0), relation (C, t_attach, left, D, E).	
<i>Rt12</i>	15	0.83	7/14	placement (A):-type (A, separation), relation (A, irreg, right, B, C), type (C, separation), relation (C, irreg, left, D, E), relation (E, bend_attach-r, top, F, G).	
<i>Rt13</i>	14	0.78	5/14	placement (A):-relation (A, irreg, left, B, C), relation (C, i_detach, top, 1, D).	
<i>Rt14</i>	13	0.72	7/14	placement (A):-type (A, wall), angle (A, 0), relation (A, i_attach, top, B, C), relation (C, i_attach, top, D, E), relation (E, irreg, left, F, G), type (G, wall).	
<i>Rt15</i>	13	0.72	9/14	placement (A):-relation (A, irreg, right, 1, B).	
<i>Rt16</i>	13	0.72	9/14	placement (A):-type (A, wall), relation (A, irreg, left, 8, B).	
<i>Rt17</i>	12	0.67	5/14	placement (A):-relation (A, vi_detach-l, root, B, C), relation (C, irreg, left, D, E).	
<i>Rt18</i>	12	0.67	5/14	placement (A):-relation (A, irreg, left, B, C), relation (C, t_attach, right, D, E), relation (E, bend_attach-r, top, F, G).	
<i>Rt19</i>	12	0.67	7/14	placement (A):-relation (A, irreg, left, B, C), type (C, wall), relation (C, irreg, right, D, E), type (E, wall), angle (E, 90), relation (E, bend_attach-r, top, F, G).	
<i>Rt20</i>	12	0.67	3/14	placement (A):-type (A, wall), relation (A, irreg, left, B, C), angle (C, 45).	

Table 1-2. Rules of trained students (continuation of Table 1-1)

RID	CE	Cov (%)	CM	Description of rules	Diagram
Rt21	12	0.67	7/14	placement (A):-relation (A, li_detach-r, root, B, C), type (C, out_door), angle (C,0).	
Rt22	11	0.61	4/14	placement (A):-relation (A, irreg, left, B, C), type (C, wall), angle (C, 90), relation (C, i_attach, top, 2, D).	
Rt23	11	0.61	5/14	placement (A):-relation (A, irreg, right, B, C), type (C, wall), relation (C, li_detach-l, top, 1, D), type (D, wall).	
Rt24	11	0.61	2/14	placement (A):-relation (A, close, none, B, C), angle (C, 0), relation (C, close, none, D, E), relation (E, irreg, right, F, G), angle (G, 0).	
Rt25	10	0.56	3/14	placement (A):-relation (A, irreg, left, B, C), relation (C, i_attach, top, 10, D).	
Rt26	10	0.56	4/14	placement (A):-relation (A, irreg, left, B, C), type (C, wall), angle (C, 90), relation (C, i_attach, root, 5, D).	
Rt27	10	0.56	2/14	placement (A):-relation (A, irreg, right, B, C), type (C, wall), relation (C, i_attach, top, D, E), relation (E, i_attach, root, F, G), relation (G, i_attach, top, H, I).	
Rt28	10	0.56	6/14	placement (A):-relation (A, irreg, right, B, C), angle (C, 90), relation (C, bend_attach-r, top, 1, D).	
Rt29	10	0.56	5/14	placement (A):-type (A, vegetation), relation (A, li_detach-l, root, B, C), relation (C, i_attach, root, D, E).	
Rt30	10	0.56	7/14	placement (A):-relation (A, li_detach-r, root, B, C), relation (C, irreg, left, D, E), relation (E, i_attach, top, F, G), type (G, wall).	

Table 2-1. Rules of untrained students: IDs of rule RID, number of positive examples covered by rule CE, coverage of rule Cov (%), number of members whose placements are covered by rule CM, description of rules, and diagram of rules

RID	CE	Cov (%)	CM	Description of rules	Diagram
Ru1	56	3.35	8/14	placement (A):-relation (A, close, none, B, C), type (C, mat), relation (C, close, none, D, E), relation (E, close, none, F, G), type (G, mat), relation (G, close, none, H, I), type (I, furniture).	
Ru2	29	1.73	4/14	placement (A):-angle (A, 0), relation (A, irreg, left, B, C), relation (C, i_attach, top, 3, D).	
Ru3	27	1.61	8/14	placement (A):-relation (A, close, none, B, C), type (C, mat), relation (C, close, none, D, E), angle (E, 90).	
Ru4	26	1.56	6/14	placement (A):-relation (A, close, none, B, C), type (C, mat), relation (C, close, none, D, E), type (E, furniture), angle (E, 0), relation (E, isolation, none, F, G).	
Ru5	25	1.50	5/14	placement (A):-type (A, furniture), relation (A, irreg, right, B, C), relation (C, i_attach, top, D, E), relation (E, li_detach-r, top, F, G).	
Ru6	21	1.26	8/14	placement (A):-relation (A, irreg, right, B, C), relation (C, li_detach-l, root, D, E), relation (E, i_attach, top, F, G).	
Ru7	21	1.26	4/14	placement (A):-relation (A, irreg, left, B, C), relation (C, i_attach, top, D, E), type (E, separation), relation (E, li_detach-r, root, F, G), type (G, wall).	
Ru8	20	1.20	8/14	placement (A):-type (A, out_door), relation (A, irreg, right, B, C), relation (C, bend_attach-r, root, D, E).	
Ru9	20	1.20	7/14	placement (A):-type (A, furniture), relation (A, close, none, B, C), type (C, mat), relation (C, close, none, D, E), type (E, mat), relation (E, isolation, none, F, G).	

Table 2-2. Rules of untrained students (continuation of Table 2-1)

RID	CE	Cov (%)	CM	Description of rules	Diagram
Ru10	14	0.84	4/14	placement (A):-type (A, mat), angle (A, 0), relation (A, irreg, left, B, C), type (C, wall).	
Ru11	13	0.78	6/14	placement (A):-type (A, wall), relation (A, bend_attach-l, top, B, C), relation (C, i_attach, root, 1, D).	
Ru12	13	0.78	4/14	placement (A):-relation (A, i_attach, top, 1, B), type (B, wall), relation (B, i_attach, top, C, D), type (D, wall), angle (D, 0), relation (D, i_attach, top, E, F).	
Ru13	13	0.78	8/14	placement (A):-type (A, wall), relation (A, bend_attach-l, top, B, C), type (C, wall), relation (C, bend_attach-r, root, D, E), angle (E, 0).	
Ru14	13	0.78	7/14	placement (A):-type (A, furniture), angle (A, 0), relation(A, semi_reg, right, B, C), type(C, wall).	
Ru15	13	0.78	5/14	placement (A):-relation (A, irreg, right, B, C), relation (C, bend_attach-l, root, D, E), relation (E, i_attach, root, 2, F).	
Ru16	12	0.72	2/14	placement (A):-relation (A, irreg, left, B, C), relation (C, bend_attach-r, top, D, E), angle (E, 45).	
Ru17	12	0.72	5/14	placement (A):-relation (A, i_attach, top, B, C), type (C, wall), angle (C, 90), relation (C, i_attach, top, D, E), relation (E, irreg, left, F, G).	
Ru18	11	0.66	5/14	placement (A):-angle (A, 0), relation (A, i_attach, root, B, C), type (C, wall), relation (C, i_attach, root, D, E), relation (E, bend_attach-l, root, F, G).	
Ru19	11	0.66	6/14	placement (A):-relation (A, li_detach-l, root, B, C), relation (C, bend_attach-r, top, D, E), relation (E, bend_attach-l, root, F, G).	
Ru20	11	0.66	4/14	placement (A):-relation (A, irregular, left, B, C), relation (C, i_attach, root, 1, E), relation (E, i_attach, root, 1, F), type (F, separation).	
Ru21	11	0.66	6/14	placement (A):-type (A, separation), relation (A, irreg, right, B, C), relation (C, bend_attach-l, root, 2, D), type (D, wall).	
Ru22	10	0.60	4/14	placement (A):-relation (A, irreg, left, B, C), relation (C, i_attach, top, D, E), relation (E, bend_attach-r, top, 2, F).	
Ru23	10	0.60	3/14	placement (A):-angle (A, 90), relation (A, irreg, left, B, C), relation (C, i_attach, top, 1, D), angle (D, 90), relation (D, i_attach, top, E, F), relation (F, bend_attach-l, top, G, H).	
Ru24	10	0.60	9/14	placement (A):-relation (A, bend_attach-l, top, B, C), type (C, wall), relation (C, bend_attach-r, top, D, E), relation (E, i_attach, top, F, G).	
Ru25	9	0.54	4/14	placement (A):-type (A, furniture), angle (A, 90), relation (A, irreg, right, B, C), type (C, wall), relation (C, i_attach, top, D, E), relation (E, i_attach, top, F, G).	
Ru26	9	0.54	9/14	placement (A):-relation (A, close, none, B, C), type (C, mat), relation (A, close, none, 3, C).	
Ru27	9	0.54	3/14	placement (A):-angle (A, 90), relation (A, irreg, left, B, C), relation (C, i_attach, root, D, E), relation (E, i_attach, root, F, G).	
Ru28	9	0.54	6/14	placement (A):-type (A, furniture), angle (A, 0), relation (A, irreg, right, B, C), angle (C, 0), relation (C, i_attach, top, 1, D), angle (D, 0), relation (D, i_attach, top, E, F), type (F, wall).	

6.2. COMPARISON OF TWO GROUPS

By comparing the rules of the trained and untrained students, four contrastive characteristics (Table 3) were found from the following two viewpoints:

1. Attributes of miniatures and relationships that are referred to in rules
2. Compressibility of the information with generalization and predictive precision of rules

The details of these characteristics are discussed in the following subsections.

6.2.1. Extension method of chain of miniatures

Ten of the 30 rules of trained students, *Rt2-4, 9, 13, 17, 21, 23, 29, and 30*, refer to noncontact relationships that indicate that the miniatures don't touch each other (e.g., "irreg," "vi_detach," "i_detach," and "li_detach"). On the contrary, only 4 of the 28 rules of untrained students, *Ru5-7, and Ru19*, refer to noncontact relationships. 21 of the 28 rules of untrained students, *Ru2, 5-8, 11-13, 15-25, 27, and 28*, refer to contact relationships that indicate that the miniatures touch each other (e.g., "i_touch" and "bend_attach"). Only 11 of the 30 rules of trained students, *Rt2-4, 9, 13, 17, 21, 23, 29, and 30*, refer to contact relationships. Fig. 8 illustrates these differences, which suggest that trained students have a marked tendency to expand the chain of miniatures by noncontact relationships and untrained students are more likely to expand the chain of miniatures by contact relationships.

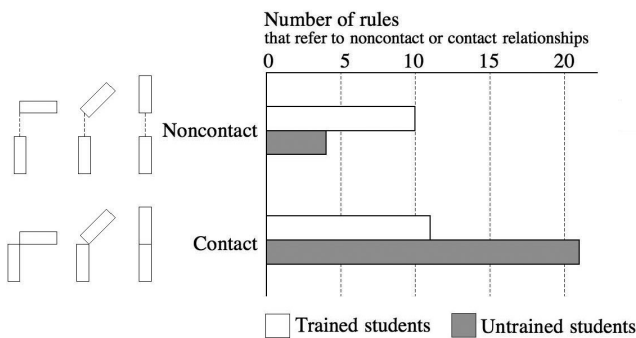


Fig. 8. Comparing numbers of rules that refer to noncontact or contact relationships

6.2.2. Relationship as basic unit of composition

Five rules of untrained students, *Ru11, 12, 20, 23, and 28*, indicate that a miniature is placed with an "i_attach" relationship with a miniature that was just previously placed. This tendency suggests that direct composition is a basic unit of the spatial composition process for untrained students.

On the contrary, rules *Rt6, 12, 19, and 24* of the trained students show that three miniatures were frequently placed with "semi_irreg" or "irreg" relationships, indicating miniatures that are parallel to each other. This tendency suggests that parallel composition is a basic unit of the spatial composition process of trained students.

6.2.3. Types of miniatures

In both groups, the type of miniature most frequently referred to in their rules is "wall." A contrastive characteristic appears in the second most frequently type of miniature mentioned, "separation," in the rules of trained students (*Rt2, 3, 8, 12*). In the

rules of untrained students, the second most frequently referred to types are "furniture" (*Ru1, 4, 5, 9, 14, 25, 28*) and "mat" (*Ru1, 3, 4, 9, 10, 26*), which have equal ranks. The type "separation" includes such vertical planes as walls, fences, and hedges, and "mat" includes such horizontal planes as carpets, grass, and tatami mats. From above, the process of enclosing and separating spaces with walls characterizes trained students, and making the surrounding living environment using furniture or mats characterizes untrained students.

6.2.4. Compressibility of information and predictive accuracy of rules

In the Progol learning of the process of architecturally trained students, 1708 of 1801 positive examples were generalized. 513 rules were constructed, and 93 positive examples were not generalized. This result means that information of the spatial composition process by architecturally trained students was compressed by generalization. Compressibility *C* is calculated by $C = (GP - R)/P$, where *GP* is the number of positive examples generalized, *R* is the number of rules, and *P* is the total number of positive examples. Large compressibility means that the spatial composition process by positive groups has strong regularity. The compressibility of trained students is $(1708 - 513)/1708 = 0.664$. For untrained students, 1509 of 1672 positive examples were compressed into 458 rules. The compressibility is $(1509 - 458)/1672 = 0.629$. We infer from this comparison of the compressibility of the two groups that the spatial composition process by trained students has stronger regularity than by untrained students.

By comparing the predictive accuracy of the two groups mentioned in Section 6.1, we recognize that predicting placements by trained students is more difficult than by untrained students.

We can interpret the differences of compressibility and predictive accuracy between the two groups as follows. Since architecturally trained students have strong regularity of spatial composition, many and various patterns appear in their processes. But their rules are so various that predicting their arrangements is difficult. In contrast, untrained student have less regularity of spatial composition and identical patterns appear many times in their processes; their arrangements are comparatively easy to predict.

Table 3 Contrastive characteristics between trained and untrained students

	Trained	Untrained
extension method of chain of miniatures	out of contact	in contact
relationship as basic unit of composition	parallel	straight
type of miniature	separation	mat and furniture
multiplicity of rules	multiple	less multiple

7. Conclusions

Inductive logic programming (ILP), which is a machine learning technique that executes inductive reasoning, was applied to the analysis of spatial composition processes using an

architectural space montage technique (ASMT).

The complexly structured data of spatial composition processes that consist of many objects, relationships between them, and their attributes were modeled in first-order logic.

One ASMT experiment was conducted with 14 architecturally trained students and 14 untrained students. These experimental cases were analyzed by Progol, which is an ILP system. 513 rules for the trained students and 458 for the untrained students were found. From these rules, contrastive characteristics were defined between the two groups from four points of view: (1) extension method of chain of miniatures, (2) relationship as basic unit of composition, (3) type of miniature, and (4) multiplicity of rules. In the future, we will analyze the spatial composition process among different cultures using our proposed method.

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