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A Computational Model for Children's Language Acquisition using Inductive Logic Programming

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Abstract

This paper proposes a computational model for children's word acquisition based on inductive logic programming. There are three fundamental features in our approach. Firstly, we incorporate cognitive biases developed recently to explain the efficiency of children's language acquisition. Secondly, we design a co-evolution mechanism of acquiring concept definitions for words and developing concept hierarchy. Concept hierarchy plays an important role of defining contexts for later word learning processes. A context switching mechanism is used to select a relevant set of attributes for learning a word depending on the category which it belongs to. On the other hand, during acquiring definitions for words, concept hierarchy is developed. Thirdly, we pursue resemblance to human brain in functional level.

We developed an experimental language acquisition system called WISDOM (Word Induction System for Deriving Object Model) and conducted virtual experiments or simulations on acquisition of words in two different categories. The experiments shows feasibility of our approach.

1 Introduction

This paper proposes a computational model for children's language acquisition in terms of inductive logic programming (ILP), based on the observation of the similarity between human learning and concept learning by ILP.

In language acquisition, there are several difficulties related to its efficiency. First, we need to formalize sensory inputs. There are many input data to be potentially used in concept learning. Human being selects only those attributes which are relevant to describe given objects. We assume that human utilize some kind of context switching mechanism to choose appropriate set of input stimuli for each learning task. Perception itself may involve learning process to select appropriate set of attributes for each learning task. Since we focus to develop computational model for human word learning, we avoid to include perception parts in our model. Instead, we carefully prepare appropriate input stimuli after perception process by hand.

The second problem is to drastically restrict search space in concept learning. In language acquisition, there are huge number of possibilities for the target of a given label. It is called Quine's paradox [11]. Aiming at solving this problem, many cognitive psychologists have been working to identify a set of constraints or biases under which children conduct supervised learning of concepts description given input sensory stimuli together with labels for target objects which their mothers, say, give to them [6, 4]. These include Whole Object Bias, Taxonomy Bias, Mutual Exclusivity Bias, the Principle of Contrast, Shape Bias and so on. Biases play an essential role in reducing search space in concept description. Without biases, there seems no hope for children to learn words concepts from a very small set of examples. The situation is similar in machine learning: bias is essential for learning concepts even for a simple propositional learner [7]. In case of inductive logic programming, there are essentially two kinds of biases: declarative (language) bias and procedural bias. Cognitive biases correspond neither to declarative nor to procedural bias, directly. They correspond to various parts in ILP procedure. For example, Shape Bias can be accommodated into inductive logic programming by defining a new evaluation function with heavier weight to shape-type attributes. On the other hand, Taxonomy Bias can be realized by introducing different evaluation functions for each task depending on the taxonomy class of the target concept.

One notable characteristics of our model is its co-evolution between *word description* learning ability and *concept hierarchy* building ability. As we state later, they are mutually dependent; word description learning utilizes concept hierarchy and conversely concept hierarchy building utilizes word description. Also, Mutual Exclusivity Bias as well as the Principle of Contrast is applied to build concept hierarchy.

We discuss some functional similarities between human brain and our computational model. We focus two points: a context switching function for selecting a relevant set of attributes for learning a word depending on the category which it belongs to, and parameter learning function in evaluation functions. The former corresponds to a switching function in human brain for selecting an appropriate motion program for performing the target task, or a target setting function for posing a problem to be further analyzed. These functions are known to be realized in paleocortex, especially at amygdaloid complex.

The latter corresponds to neural network learning in the brain, either in cerebrum or in cerebellum.

We built a preliminary computational model of children's noun acquisition and conducted virtual experiments by giving a set of attribute-value pairs as input stimuli together with a label to perform supervised learning.

In section 2, constraints theory in cognitive science for acquiring noun is introduced. In section 3, a computational model for children's noun acquisition based on ILP is presented. In section 4, the results of virtual experiments are described. In section 5, related work is briefly mentioned. Finally, in section 6, conclusion and future research direction are given.

2 Constraints Theory in Cognitive Science

Designing a mechanism of human language acquisition has ever been addressed as an extremely difficult problem.

Induction is deeply tied with learning, so we want some noun learning model utilizing induction. However, when we try this, we found difficulty in intensional description of concepts. Intension of a cat is an answer for the question 'What is a cat?'. A cat has furred skin, has four legs, is good at climbing trees, can reach its hind feet to back of its ears, etc. Then, what is the sufficient set of descriptors? How can children find such a set?

Markman [6] suggested Constraint Theory on vocabulary acquisition by human children. What she constrained is children's expectation for the questions 'What is named?' and 'How the things to be named should be selected?'.

We use nouns for varied types of intensions. We use 'a cat' or 'a car' to indicate a concrete or an imaginary object from a certain category which we think we know what it is. The words 'you' and 'them' changes their target object/s depending situations. 'Mr. Smith' and 'John' indicates a fixed target in a speaker's community. 'water' and 'rice' has neither their shapes nor their ends. Consider the characteristics of following words: 'a finger', 'the ground', 'a forest', 'machinery'.

Although we human beings have such a large number of types of nouns, we do learn nouns only from positive examples. The universe of names is complex as you see, but this observation is static and comes from matured language. Constraint Theory is a hypothesis on a stepwise acquisition of vocabulary and can be regarded as defining priority on category types, in general.

Whole Object Bias [6] is a bias Markman herself suggested under the Constraint Theory. This bias states that a child considers the novel label refers the whole of a given related object if it is unnamed. This means that an unnamed object requires a label for its whole object primarily. We can use such a bias as a constraint for setting the whole object as the one to be referred to by labels.

Other biases we try to assemble in our learning model than Whole Object Bias include: Taxonomy Bias, Shape Bias, the Principle of Contrast, and Mutual Exclusivity Bias.

Taxonomy Bias [6]: This bias states that a child tends to interpret a label, to be mapped to some category, to include a related object. This means that children know that the relation between label and the referred objects is not bijective. In fact, children do generalize a known label to map to objects that are not identical to the one which they saw when they were learning the label.

It is important to consider another aspect of Taxonomy Bias. According to [1], children recognize animals as analogical beings of human beings or children themselves. Some children confess that plants are not living because they do not move; some others say that insects have their heart. These misunderstanding shows their knowledge that some objects are alike to human beings while the others are not. This knowldege is referred to as an ability of classifying object taxonomies.

Shape Bias citeHI90: This bias states that children think objects are similar when their shapes are similar. Children tend to generalize a label of an object to a concept having similar shape.

The Principle of Contrast: This bias states that children tend to think different labels can refer to the same object, yet their sets of referring objects cannot be identical.

Mutual Exclusivity Bias [6]: This bias states that children tend to think different labels do not refer to the same object.

3 A Computational Model for Children's Language Acquisition in ILP

We show the configuration of WISDOM (Word Induction System for Deriving Object Model), our computational model for the childrens' word (noun) acquisition in figure 1. We use the name 'WISDOM' to refer to our computational model as well as to its implementation. The detailed descriptions of their modules are described below. Note that Label Input Module and Sensory Input Module are not implemented here in WISDOM. They are virtual modules.

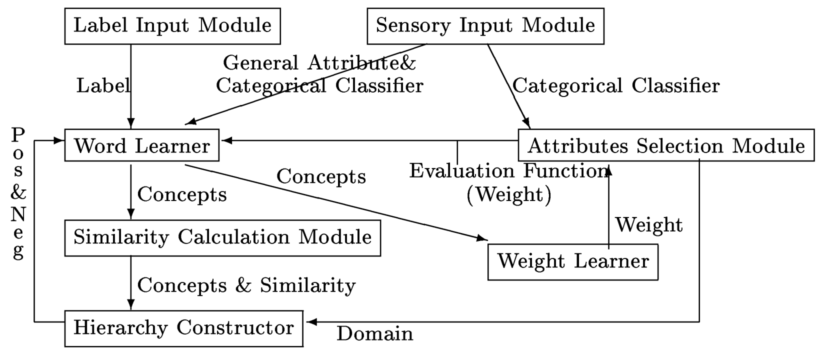

Figure 1: Configuration of our word acquisition model WISDOM

3.1 Learning Attribute Relevancy (Sensory Input Module, Attributes Selection Module)

As mentioned in section 1, there are many input data to be potentially used in concept learning. Human being selects only those attributes which are relevant to describe given objects. In order to model this feature, we designed a mechanism for selecting an appropriate evaluation function from a set of functions prepared for each category. It is a kind of switch box controlled by categorical information of the object to be learned. Each evaluation function in turn is a linear combination of relevant attributes to the corresponding category. In order to model the learning capability of relevant attributes selection which human perception mechanism realizes, we need to incorporate Weight learning in evaluation functions (Weight Learner). In our first experiment, we predefined those weights by hand. The automatic weight adjustment is one of our future research targets.

Note that this mechanism should avoid the difficulty of bridging objects perception and words acquisition.

3.2 Inductive Learning of Concept Definition (Word Learner)

ILP [8, 2] is a framework for learning relational concepts when a set of positive and negative examples are given together with background knowledge in the form of horn clauses. More precisely, ILP searches the concept lattice formed by the combinations of background knowledge, and finds the best hypothesis which explains most of the positive and few of the negative examples together with background knowledge. On one hand, the standard ILP systems require at least several positive and negative examples before learning, and those adopt compression gain, or the MDL principle as the evaluation function. On the other hand, the system in our ILP model for the children's vocabulary acquisition continuously repeats the generation and revision of the concept description during the life time. It can work even if only one or few examples are provided because a new evaluation function reflecting the cognitive bias is implemented.

We briefly explain how actual word learning corresponds to ILP in our model. We assume that children can correctly identify the object with which the word *i.e.* label is associated. Note that the label is given separately by, say, their mother as oral signal (Label Input Module). The properties of the object are divided into two kinds, which we call *Categorical Classifier* and *General Attribute*. Categorical Classifiers correspond to children's innate ontology, thus they indicate ontological categories such as 'animate', 'countable', etc. General Attributes such as 'having-four-legs' or 'furred' include all objects properties other than those represented as Categorical Classifiers. The General Attributes are further divided into some subtypes such as shapes, colors, textures, etc. Based on these assumptions, we feed both observations (sensory inputs) on an object and a label on it to the system in the form of logical formula which ILP can directly handle.

Since each label presents the category to which the object belongs, the concept to be learned is indicated by the label. The objects are given as examples and their properties are given as background knowledge. When the system takes an object and its label as a pair (we call them current object and current label respectively), the system learns or revises the concept indicated by the current label by generalizing the current object if necessary. At this time, the current object and all objects named by the current label (which are given in the previous learning processes) are used as positive examples. The negative examples are selected from the rest of the examples based on word learning biases.

The concept hierarchy is utilized for providing further positive and negative examples. For example, positive example objects for a subordinate category of the current label are regarded as positive examples for the current label. Contrastly, negative examples for a superordinate category are regarded as also negative for the current label.

In our model the concepts are learned in two steps. First, the model determines a *Supercategory* or a domain for the label using the Categorical Classifier/s of the current object. Then, relevant General Attributes for the Supercategory are selected for generalization of the given example.

Obvious benefit of adopting the above two-steps procedure is that one can reduce relevant background knowledge in computing generalization.

Furthermore, it reduces the hypothesis space by restricting negative examples to only meaningful ones. Let us consider the case in which we learn a concept 'cat'. Assume that the given object named cat has 'animate' as its Categorical Classifier and 'having-four-legs' as its General Attribute. Assume also that an object having a label 'desk' has already been given in the previous inference process and it had 'having-four-legs' and 'inanimate' as its General Attribute and Categorical Classifier respectively. In this case, although the object named 'desk' is obviously negative example for the concept 'cat' because the label is different, the model excludes this object from the negative examples for learning because the Categorical Classifiers 'animate' and 'inanimate' are mutually exclusive. If this dynamic selection of negative examples could not be done, the concept 'cat' could not have been inferred because the property 'having-four-legs', which may be crucial for this concept, could not be included in the definition of 'cat'. Furthermore we can reduce the hypothesis space by excluding the candidates having Categorical Classifiers used in selecting negative examples.

3.3 Role of bias in ILP and Realization of Constraint Theory

Cognitive biases correspond neither to declarative nor to procedural biases in ILP directly. We describe how the cognitive biases are implemented in this subsection.

Let us consider a part of the 'reference problem' of the word acquisition. When a label is associated with an object, what aspect of the object should the label be mapped on to? This is an essential problem for our model because it determines kinds of concept our model can learn. In our current design, the model assumes that every label refers to the entirety of an object according to Whole Object Bias (see section 2). Therefore the model can learn only labels of objects as a whole, while it cannot learn other kinds of concept such as a property or a part of object, an action, an event, and so on. For example, the word 'dog' and 'desk' can be learned, but the word 'ear' (the part of object) and 'running' (the action) cannot be learned.

The first feature of Taxonomy Bias, the tendency of generalization, is automatically implemented in our model because ILP by its nature is used for generalization. That is, the model automatically assumes that a label refers to a category. The second feature, the ability of restricting learning domains, is realized by Domain Selection Module.

When two labels are judged to be not similar by Shape Bias, the model obeys Mutual Exclusivity Bias and the labels are not allowed to share the same object. On the other hand, when two labels are judged to be similar by Shape Bias, the model obeys the Principle of Contrast and the labels are allowed to be hierarchically related.

In our model, the evaluation criterion is introduced so that it reflects the Shape Bias. This allows the model to select an appropriate hypothesis even if only few positive examples are given. Like an ILP system Progol, this evaluation criterion is basically based on the description length of the concept, but some weights are added to each atom consisting of the concept. In our current implementation, the weight of a General Attribute about shape is set 1.5 times heavier than that of an other type General Attributes, and the weight of a Categorical Classifier twice heavier than that of a General Attribute.

When we learn the concept belonging to a Supercategory or a domain CC_j in the children's innate ontology, the general expression of our evaluation function is defined as:

$$C_{CC_j} = -PE + NE - w_{CC} * |CC_j| - \Sigma_i \ (w_{GA}^{CC_j,i} * GA_i)$$

where PE and NE are the number of positive and negative examples explained by the candidate hypothesis respectively; $|CC_j|$ and w_{CC} are the number of the Categorical Classifiers appearing in the candidate hypothesis and the uniform weight of Categorical Classifiers, respectively. GA_i and $w_{GA}^{CC_j,i}$ are the number of the General Attributes whose subtype is i in the candidate hypothesis and the weight of a General Attribute of that subtype, respectively.

In this evaluation function, Shape Bias can be realized by putting the heavier weight on the attribute about shape as mentioned earlier. We can also realize some kind of context switching mechanism, *i.e.* Taxonomy Bias by introducing different sets of evaluation functions and weights for each task depending on the Supercategory of the target concept. By the way, Shape Bias is not always applied. With the increase of conceptual knowledge, children gradually come to realize that shape similarity is not the most essential factor for determining the membership of an object category. We believe that this bias shift can be simulated by weight learning in the evaluation function.

3.4 Building Concept Hierarchy (Hierarchy Constructor)

As mentioned in section 2, we human beings have knowledge called taxonomy on concepts universe. Materials (like water or rice) are different from shaped objects (like a car or a cat) in the aspects to be referred by labels. In vocabulary acquisition, it is not the issue to classify them; yet the issue is to differentiate water from rice, and also car from cat. The shape of the whole object makes no sense when we separate rice from water, while the probability that an arbitrary car and an arbitrary cat have the same shape is very low.

So, first of all, children need to distinguish materials from objects before they learn vocabulary. We refer groups like materials or objects as taxonomy class or *Supercategory*. Supercategories which dominate large part of vocabulary universe, such as the ones given above, may be known to children prior to language learning. Experiments involving infants provided some evidence for this [3].

On the other hand, at the lower level of taxonomy, that is, at rather more concrete parts of vocabulary universe, we cannot give a priori categories. For example, artificial tools used in our daily life are classified in various categories. A flower pot is similar to a bowl for dietary use in shape, though the former has hole/s to let water flow out. The former appears in scenes of gardening, while the latter does in meals. We must have learned such categories through the daily life. In other words, such categories are culture-dependent. Flower pot category and bowl category are both created and developed under the Supercategory of shaped objects. What we refer as concept hierarchy building includes such introduction and following updates of low-level, local and cultural categories.

Note that culture-dependent categories include universal ones. As shown in section 2, some children think that plants are non-living, but in any culture on the planet plants are separated from non-living things like rocks.

The existence of a higher level Supercategory for the concept to be learned helps a lot in learning its definition. 'A cat' is learned as a concept within the Supercategory of living animate objects, while 'a bowl' is non-living static objects. Children also know that both of them refer concepts within the shaped objects' Supercategory. Such knowledge prevents children from diffusing into irrelevant attributes during object analysis. When children see a bowl related with a label 'bowl', they analyse its shape, and possibly, other additional attributes like its material, location and so on. In order to observe and analyse its properties, they may give it pressure with their fingers, palms, or teeth; they may rub it with their dry and/or wet fingers; or they may taste it with their tongues. However, they do not observe its way of locomotion. They interpret that locomotion is irrelevant as soon as they see the object.

Concept hierarchy is basically united knowledge of hierarchical relations among named concepts. Assume that a child knows the following things: first, a 'dog' is an 'animal'; second, a 'terrier' is a 'dog'. From these propositions, the child can tell that a terrier is an animal. This inference is purely deductive. Note that no sensory device is needed in such inference.

This is an important competence for human beings to understand his or her environments. Our knowledge includes tacit component, like the judging ability whether a given object is a dog, which occupies large parts in our entire knowledge. However, explicit pieces of distributed knowledge such as relationships among labeled concepts are integrated to systematic knowledge by conducting logical inference.

Concept hierarchy enforces vocabulary developing. Recall that children are supported by database which include domain-specific heuristics in learning new names. Concept hierarchy conveys properties of higher concepts to lower concepts. Suppose a child knows what a 'dog' is and an adult comes to tell him 'That is a terrier.' pointing a dog. Unless he adopts Mutual Exclusivity Bias for this accident, he may interpret a 'terrier' is another name of the object, and may think that the category 'terrier' differs from a 'dog', encompassed by the Principle of Contrast.

The previous story of a dog labeled 'terrier' shows a typical example of hierarchical relationship between two objects. Suppose the learner already knows one of these two concepts, and then sees the other. In hierarchical case, since one of them includes the other, it is typical that the pointed object already has a label.

We show representation of one of such cases in our model. On the top of figure 2, a learned concept intension corresponding to a known label `dog` is shown. Next three clauses are observations on objects `obj001, obj002, obj003`. Assume that each of these was related with the label `dog` when it was observed. Novel category names can be introduced referring to one of these objects. Such a name can be `cat`, which should be mutually exclusive with `dog`; or `terrier`, which should be subordinate of `dog`.

Suppose that one of such labels is newly introduced related only one of these three objects in input, and that the learner then learns a concept named by this label. The learned concepts are also shown in figure2 below the list of observations on the objects. Note that we need to identify the case either 'mutually exclusive' or 'subordinate'. For this purpose, we employ a kind of similarity measure (Similarity Calculation Module). If the similarity between the concept `dog` and the introduced one is small, the learner would

```
 (Intension of dog)
 labeling(dog, A) :-
          tax(A, animation, animate),  attr(A, shape, short_tail).

 (Observations of objects)
tax(obj001, animation, animate).   tax(obj002, animation, animate).
attr(obj001, shape, hanging_ears). attr(obj002, shape, short_tail).
attr(obj001, covering, furred).    attr(obj002, shape, hanging_ears).
tax(obj003, animation, animate).
attr(obj003, shape, short_tail).
attr(obj003, covering, furred).

 (Derived intensions)
 labeling(label001, A) :-
          tax(A, animation, animate),
          attr(A, shape, hanging_ears),  attr(A, covering, furred).
 labeling(label002, A) :-
          tax(A, animation, animate),
          attr(A, shape, short_tail),  attr(A, shape, hanging_ears).
 labeling(label003, A) :-
          tax(A, animation, animate),
          attr(A, shape, short_tail),  attr(A, covering, furred).
```

Figure 2: List of intension of `dog` and observations for 3 objects

interpret that they are hierarchically related, according to the Principle of Contrast and Taxonomy Bias. Or, if the similarity is large, he would interpret that they are mutually exclusive based on Mutual Exclusivity Bias.

These three objects have differences on *how much typical* `dogs` they are. The intension of `label001` relating only with `obj001` seems the least similar to the concept intension of `dog`. In other words, `obj001` seems the *least typical* `dog` of the three, since there appears no General Attribute descriptor `short_tail` in its observation. Of the rest two objects, `obj002` seems a less typical `dog`, because there appears a different descriptor `hanging_ears` from `short_tail` on `shape` dimension. It follows that the last object `obj003` seems the most typical of three. Accordingly, it should lead to the following result: the new label related with `obj001` would get the smallest similarity between the intensions of the `dog` and the one related with `obj003` would get the largest similarity.

We assume that the similarity between two learned concepts is inversely proportional to the *concept distance* between their intensions. Concept distance between two concept intensions is measured basically by the number of descriptors which occur in one concept intension but do not in the other. Descriptors are weighted based on their importance. First, Categorical Classifiers (represented in the predicate `tax`) are counted 2 times more than basic `attr` predicate descriptors. Additionally, General Attributes (represented in `attr` predicate) can have varying scores by different kind attributes of the descriptor. For example, in the Supercategory `animate`, we put 1.5 points per one difference on `shape` dimension than the other `attr` predicates.

In this case, we count that difference of existence of General Attribute `furred` on `covering` as 1 point. And we give weights for other descriptors as mentioned above: General Attributes on `shape` are given 1.5 points, while Categorical Classifiers are given 2 points. Similarities between `dog` and the newly introduced categories become as follows: 0.25 with `label001`, approximately 0.67 with `label002` and 1.00 with `label003`, respectively.

We let the model judge whether the relation with `dog` is hierarchical for each object by similarities calculated above. Giving threshold, below which the relation is interpreted mutually exclusive and above which it is interpreted hierarchical, is a simple method. In this case, we set the threshold at $0.17 = 1/6$. This threshold allows us to admit the total occurrence of supportive attributes to the target category up to four less than that of non-supportive ones. [1]

It leads that all three introduced categories are interpreted as being hierarchically related with `dog`. `label001` is difficult to judge at current status, but more information and further learning process may be necessary to verify the judgement.

Our computational model WISDOM creates and revises hierarchical and mutual exclusive relations between concepts through the successive learning. The whole of such relations represents knowledge of concept hierarchy.

3.5 Co-Evolution of Concept Learning and Concept Hierarchy Building

One of the most characteristic features of our model is the co-evolution of concept learning and concept hierarchy building. Concept learning and concept hierarchy building corresponds to two different learning activities: concept learning is achieved by supervised learning whereas concept hierarchy building is achieved by a kind of unsupervised learning. In concept learning phase, concept hierarchy helps in identifying the Supercategory which the target object belongs to and therefore in choosing an appropriate set of attributes to classify it. On the other hand, in concept hierarchy building, the definitions of related concepts can be used to build concept hierarchy. One possible trigger to build concept hierarchy is during concept learning when we apply the Principle of Contrast by assigning either super class category or subordinate category to the labeled object to be learned.

4 Virtual Experiments

In this section, we compare two learning experiments by WISDOM. These two experiments differs from each other in ontological domain. The domain of the first experiment is of tools that we use when we have meals. The domain of the other experiment includes animal categories. We intend to find difference between sets of attributes used in intensions of named categories from each other. Each specific domain may be characterized by a set of attributes used in explaining named categories.

In the first experiment, we provide two examples to WISDOM. One is on a fork and the other is on a spoon. These two instruments are from the same dining set. Both are made of stainless steel, have almost the same length (19cm) and have handles in the same design. Then WISDOM tries to make distinction between them by comparing the part having contact to foods.

The input list for the fork given to WISDOM is shown in figure 4. They are the first stimuli for the entirely novice learner. The first clause in the list says that the appearing object is called a `fork`. The third term of this and the next clause shows that this information is the first and the latest for the learner.

[1]Precisely speaking, we sum up the attributes weights. Since 4 times 1.5 (the shape score) is 6, the inverse becomes 1/6.

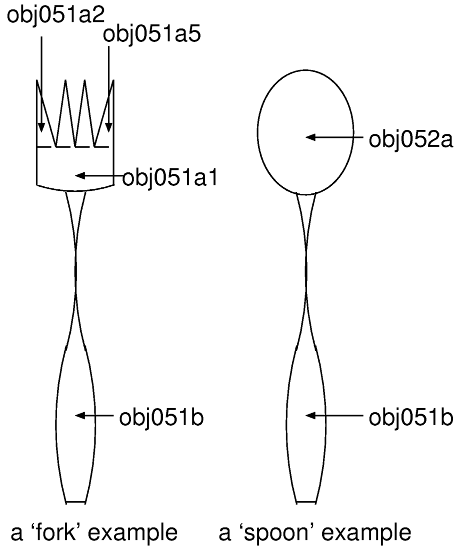

Figure 3: Example objects `obj051` and `obj052` for the labels `fork` and `spoon`

The clauses in figure 4 represent perceptual information on the object on the left of figure 3. Assume that the object is put on a table with the handle near to our body. The third clause whose predicate is `tax` says that the object is not animate. The following 4 clauses with the predicate `attr` give information on the whole object. Next 3 clauses with the predicates `subobj` and `connection` say that the object has two parts connected to each other with front-to-back placement. `obj051b`, the handle of the fork, is in contact with the rest part at its backend (`y_plus`). The rest 20 unit clauses of the list represent observations on part of the object.

After giving this input list to WISDOM, we let it start to learn. WISDOM is set to induce the rule of `labeling` given latest. So it induces the condition concluding `labeling(fork, X)`. Selection of the most preferable hypothesis is done based on the hypotheses evaluation function. The result is shown in figure 4.

Although we omit the detailed input data for the spoon here, the reader could easily imagine how they look like. They are similar to those for the fork; the handle is represented in the same formalization and the rest part is represented additionally. We only note that the spoon is given the object identifier `obj052`.

After learning `fork`, we give the input data for the spoon and let the learner to learn again. The result is shown in figure 5.

After starting the learning, WISDOM constructs a hypothesis. The `obj052` (a spoon) is of course used as a positive example. Note that `obj051` is used as a negative example, because the learner interprets those except explicit positive ones as negative examples by default.

Then the learner, WISDOM, tries to guess what the appearing object is called. This is done by applying all rules whose head predicates are `labeling` to `obj052`. Note that the current rule for the category `fork` is strong; it says that every inanimate object is a fork. This suggests that `obj052` is called a `fork` as well as a `spoon`. However, the learner was given that `obj052` was not a positive example for the category `fork`, so it

(Input on the fork object `obj051`)

```
labeling(fork, obj051, 1). newest_labeling(1).
tax(obj051, animation, inanimate).
attr(obj051, color, having_reflection).
attr(obj051, color, shining).  attr(obj051, shape, constant).
attr(obj051, direction, y_axis).
subobj(obj051a, obj051).  subobj(obj051b, obj051).
connection(obj051a, y_minus, obj051b, y_plus).
attr(obj051b, direction, y_axis).  attr(obj051b, shape, board).
attr(obj051b, shape, x_axis/[y_plus, y_minus]).
subobj(obj051a1, obj051a).  subobj(obj051a2, obj051a).
subobj(obj051a3, obj051a).  subobj(obj051a4, obj051a).
subobj(obj051a5, obj051a).
connection(obj051a1, x_minus_y_plus, obj051a2, y_minus).
connection(obj051a1, y_plus, obj051a3, y_minus).
connection(obj051a1, y_plus, obj051a4, y_minus).
connection(obj051a1, x_plus_y_plus, obj051a5, y_minus).
attr(obj051a2, direction, y_axis). attr(obj051a2, shape, pyramid).
attr(obj051a3, direction, y_axis). attr(obj051a3, shape, pyramid).
attr(obj051a4, direction, y_axis). attr(obj051a4, shape, pyramid).
attr(obj051a5, direction, y_axis). attr(obj051a5, shape, pyramid).
```

(Result of the first induction)

```
labeling(fork, A) :- tax(A, animation, inanimate).
```

Figure 4: Input and output on the object `obj051` associated with the label `fork`

```
labeling(fork, A) :- tax(A, animation, inanimate).
labeling(spoon, A) :-tax(A, animation, inanimate),
         subobj(B, A), attr(B, shape, oval_semisphere).

obj052 is a fork.
obj052 is a spoon.
Need induction for [fork].

labeling(spoon, A) :- tax(A, animation, inanimate),
         subobj(B, A), attr(B, shape, oval_semisphere).
labeling(fork, A) :- tax(A, animation, inanimate),
          subobj(B, A), subobj(C, B), attr(C, shape, pyramid).

obj052 is a spoon.
Need induction for [].
```

Figure 5: Result list of learning the label `spoon` after learning `fork`

(Acquired description for `cat`)

```
labeling(cat, A) :-tax(A, animation, animate).
```

(Result of learning `dog` over the knowing `cat`)

```
labeling(cat, A) :- tax(A, animation, animate).
labeling(dog, A) :- tax(A, animation, animate),
         subobj(B, A),attr(B, direction, z_axis).

obj032 is a cat.
obj032 is a dog.
Need induction for [cat].

labeling(dog, A) :- tax(A, animation, animate),subobj(B, A),
         attr(B, direction, z_axis).
labeling(cat, A) :- tax(A, animation, animate),
         attr(A, shape, barrel).

obj032 is a dog.
Need induction for [].
```

Figure 6: List on animate categories learning

```
labeling(dog, A) :- tax(A, animation, animate),subobj(B, A),
         attr(B, direction, z_axis).
```

Figure 7: Result explanation on `dog`

thinks that the rule on `fork` is not correct any longer. It starts learning the category `fork` again, with no additional stimuli to obtain more reasonable rule for the fork.

Then we proceed to the second experiment. Figure 6 shows the result of the experiment. In this experiment, we provide inputs for two animal instances; a cat, and a dog. This learning is independent from the former experiment. Like the experiment of dining instruments shown above, the learner starts from the status where it does not know any of labeled categories.

At one time, the information for one object is given, as the experiment shown above. The first input list is for the cat, and the second is for the dog. The given lists are not shown because of space limitation, but they represent their shapes in detail like the dining instruments experiment, and their colors. Additionally, `covering` attribute is used. The cat is laid on the ground, while the dog stands.

After learning the category `cat` from the first stimuli set for the cat, WISDOM acquires the knowledge shown in figure 6.

By giving inputs for the dog to the learner having this knowledge, the rule (shown in figure 7) is learned.

Both a cat and a dog have their heads, four legs, and tails. In this aspect, they have same parts of their bodies, while each corresponding parts have difference.

In this experiment, the difference in posture and figure appears. The direction `z_axis` is of a leg of the standing dog; the cat is laid and its legs are along `x` and `y` axes. Shape `barrel` is of the trunk of the cat; the dog has no part whose shape is barrel.

If we give more examples in which animals make varied postures, the attribute which represent their shapes of their heads should play more central role.

In this section, we showed knowledge acquired as results of 2 cases. Let us compare these results. The spoon and the fork has same attribute value on their surfaces, so their difference appears in shapes of parts. The learner picks the fact up that the spoon has a part whose shape is `oval_semisphere`, while it concerns that the fork has a part whose shape is `pyramid`. This pyramid-shaped part is a part of a part of the whole, so difference of `connection` structures between instruments seems important. In the latter experiment, the model concerns on the standing leg/s of the dog and the shape of the cat's trunk.

The information relating to shape is used in both results. Such information includes shape name attribute, direction of whole or partly objects, connectivity among parts of an object, relative lengths along axes of one object, relative size between different objects, and so on. Detailed analysis down to objects' parts seems effective, especially where the model is given shape-relating input information.

Description like 'object obj001 has four legs' is difficult to use in category induction even the learner knows what a leg is, for two instances of animals can be quadruped having different position, shapes of legs. Such minor difference seems to be important for differentiating categories.

5 Related Work

Our study is a proposal for computational model of children's language acquisition. Several researchers are proposing alternative methods focused on various aspects of this problem.

Siskind [12] proposed a logical induction system, which is named MAIMRA. It accepts a *scene* consisting of serial *snapshots*. Through the learning process, word labels are inductively associated with certain status changes implicitly appearing in scenes.

Munro et al. [9] constructed a neural network which learns the meanings of *propositions*. This network shows the ability to associate multiple meanings to one label, e. g. 'cracks *in* a cup' and 'a boat *in* the lake', and to output the labels at a proper context.

Both of them let the learner to construct the meaning from a given set of attributes. They do not give unnamed complete concept.

Nakagawa et al. [10] conducted interesting experiment where the machine learner (1) segments given voice and extract the referring labels and (2) constructs referred meaning from attributes in a scene. Although they give only a constant set of attributes, it is outstanding because they realized the co-evolution between concept construction and label extraction.

Our approach intends to let the machine learner to learn the concept inductively, which is similar to those studies mentioned above. Comparing to others, we originally implement *biases* suggested in cognitive science. Additionally, we stress on the learning process where concept acquisition and concept hierarchy construction help each other. Inductive logic programming seems to provide the most appropriate framework for such knowledge.

6 Conclusion and Future Work

This paper presented a computational model WISDOM for children's language acquisition using ILP. We proposed a model consisting of two parts;

concept learning and concept hierarchy building. In the model, we incorporated cognitive constraints or cognitive biases such as Taxonomy Bias, Shape Bias, Mutual Exclusive Bias and the Principle of Contrast to reduce search space in building concept description.

In concept learning, we adopted the learning scheme of Inductive Logic Programming to induce associations between the target concept and various knowledge which children acquired in the past.

In concept hierarchy building, we introduced a kind of similarity measure to judge 1. whether the given target object belongs to some category or not and 2. whether a given label to the target denotes a superordinate or subordinate concept to the conflicting category.

In WISDOM, concept learning and concept hierarchy building co-evolve each other. This feature is very important because it drastically accelerates the learning ability. The usage of taxonomy information in learning phase introduces the notion of context because each Supercategory defines each context in which concept learning becomes a relatively small and easy task.

We built a learning program (we call the program as WISDOM also) based on our model and simulated language learning tasks for two animals and also for two dining instruments.

In these experiments, we gave shape attributes in detail. We found that we needed different attributes sets for these two tasks. Furthermore we found that common attributes like having-four-legs do not work in differentiating concepts in a domain, but rather subtle attributes such as the shape of trunks are crucial.

We also noted the importance of selecting a relevant domain not only for reducing the entire search space but also for eliminating irrelevant negative examples, which made it even possible to learn the right concept efficiently.

We applied a simple similarity measure to judge whether two concept descriptions refer to distinct objects or hierarchically related objects. We could not distinguish three cases in our experiments. One reason may be due to too simple similarity measure. In our future research, we are planning to adopt further sophisticated similarity measure to improve the performance. Another reason may be lack of experiences of the system. It may resolve conflicts in such judgement by further experiments.

Another point is a set of weights assigned to different attributes. There are no strict reasons why we put score 2 the Categorical Classifiers, score 1.5 for shape attributes and 1 for the rest. We need to find appropriate numbers for these weights to establish the better solutions or better behaviors of the system. It is a weights-adjusting problem and many algorithms are known to perform such tasks.

One of our future work is to incorporate human brain functional architecture for performing learning. It consists of various components including cerebrum, cerebellum, and paleocortex. To allocate different learning styles conducted by cerebrum and cerebellum to different parts of our system is one of the problems in the incorporation. Since learning in cerebellum is simpler and more related to attaining efficiency, simple tasks associating input stimuli with their corresponding labels could be realized finally using cerebellum-type efficient learning. On the other hand, at the beginning of learning, many input stimuli are investigated. Those activities fit rather to cerebrum-type learning. For the super category selection, the process is deeply related to the activity of paleocortex. The parameter adjustment for the selection is considered as meta-learning of the evaluation function in machine learning. This is one of the most attractive features to be pursued both in machine learning and in human brain.

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