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A Bootstrapping Model for Children's Vocabulary Acquisition using Inductive Logic Programming

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Abstract

This paper proposes a bootstrapping model for children's word acquisition based on inductive logic programming. There are four fundamental features in our approach. Firstly, we address the issue of bootstrapping in children's word acquisition. We do not depend on any knowledge other than innate abilities in word acquisition process. Secondly, we incorporate cognitive biases developed recently to explain the efficiency of children's language acquisition. Thirdly, 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. Fourthly, 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 using 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 beings select only those attributes which are relevant to describe given objects. We assume that humans utilize some kind of context switching mechanism to choose an appropriate set of input stimuli for each learning task. Perception itself may involve learning process to select an appropriate set of attributes (input stimuli) [1] for each learning task. Since we focus to develop a computational model for humans' word learning, we avoid to include perception parts in our model. Instead, we carefully prepare appropriate input stimuli after perception process manually.

The second problem is to achieve drastic reduction of search space in concept learning. In language acquisition, there is a huge number of possibilities for the target of a given label. It is called Quine's paradox [11]. In an attempt to solve 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 [6, 4]. These include the Whole Object Bias, the Taxonomic Bias, the Mutual Exclusivity Bias, the Principle of Contrast, Shape Bias and so on. Word learning biases play an essential role in reducing search space in concept description. Without such biases, it seems extremely hard for children to learn words and concepts from a very small set of examples in bootstrap learning. The situation is similar in machine learning: biases are 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 do not directly correspond to declarative or procedural bias. They correspond to various parts in the ILP procedure. For example, the 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, the Taxonomic Bias can be realized by introducing different evaluation functions for each task depending on the taxonomic 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; the word description learning utilizes concept hierarchy and conversely the concept hierarchy building utilizes word description. Also, the Mutual Exclusivity Bias as well as the Principle of Contrast is applied to build a 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 ana-

[1] Since children are unconscious in what kinds of attributes are used in word acquisition, the selection of attributes means the automatic selection of relevant input stimuli in sensory nerve system.

lyzed. 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 bootstrapping model of children's noun acquisition called WISDOM and conducted virtual experiments by giving a set of attribute-value pairs as input stimuli together with a label per each session to perform supervised learning.

In section 2, constraints theory in cognitive science for acquiring noun is introduced. In section 3, a bootstrapping 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

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

Induction is deeply tied with learning, so we would like to build 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. This theory constrains children's expectations like (1) kinds of things to be referred by labels; and (2) priority of naming among such kinds or among things in a kind.

We use nouns for different 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' do not have fixed shape. Here are example words from varied types of noun: 'a finger', 'the ground', 'a forest', 'machinery'.

Although we human beings have such a large number of types of nouns, we learn nouns only from positive examples. The universe of names is complex as we saw above, but this observation is static and comes from matured language. The Constraint Theory is a hypothesis on a bootstrapping acquisition of vocabulary and can be regarded as defining priority on category types, in general. In the following paragraphs, we explain biases under this theory, and mention some notable points relating each of them.

The Whole Object Bias [6] is a bias Markman herself proposed under the Constraint Theory. This bias states that a child assumes a novel label to refer the whole of a given related object. 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 include: the Taxonomic Bias, the Shape Bias, the Principle of Contrast, and the Mutual Exclusivity Bias.

The Taxonomic Bias [6]: This bias states that a child tends to map a label to a taxonomic category which includes a referred object. This means that children know that the relation between labels 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 the Taxonomic Bias. According to [1], children recognize animals as analogical beings of human beings or children themselves. Some children say that plants are not living because they do not move. Such 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.

The Shape Bias [4]: 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 that different labels can refer to the same object, yet their sets of referring objects cannot be identical.

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

Biases explained above has been testified through numerous experiments conducted by researchers of cognitive science. It is desirable for us to let our model learner learn the same set with such experiments. However, in current phase, the learner does not have competence to accept input which children recognize. Human children seem to develop their perception ability days after days. Such development is concerned with training of perception, which may includes feedbacks from concept learning. We have not studied to identify how such perception ability would be developed yet. It is our future work.

The way we can take is to testify the behaviour of the model learner using testified biases. We check whether learning is proceeded when applying these biases.

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

In this section, we propose the configuration of WISDOM (Word Induction System for Deriving Object Model), our computational bootstrapping 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 in WISDOM. They are virtual modules, and inputs to be generate by them are given manually. As we mentioned at the end of the previous section, such modules playing roles of perception should include feedback processing from noun learner modules in their mechanism.

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 beings select 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

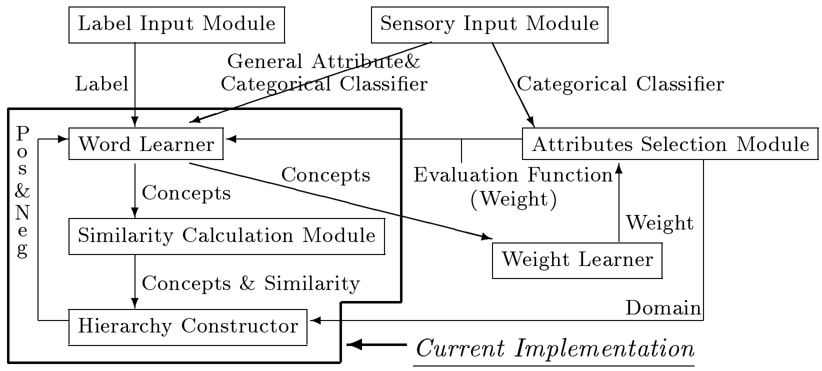

Figure 1: Configuration of our word acquisition model WISDOM

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 manually. 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.

Another important aspect of input data is its fuzziness. In our approach, we assume that input stimuli are discretized and no fuzziness is admitted. This would cause problems in matching input data to rules. However, our approach admits errors in matching by revising wrong category description learning based on further learning processes on additional examples. In future, there is a possibility to incorporate uncertain input stimuli by formulating them in terms of probabilistic logic.

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 least 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 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 a label *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 object 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. In contrast, 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*, which is a domain for the label using the Categorical Classifier/s of the current object. Then, relevant General Attributes for the Supercategory are selected for the generalization of a given example.

The 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 do not correspond directly to declarative or to procedural biases in ILP. We describe how the cognitive biases are implemented.

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 onto? 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 the Taxonomic Bias, the tendency to generalize the label to other like objects 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, that is, the ability of restricting learning domains, is realized by Domain Selection Module.

When two labels are judged to be not similar by the Shape Bias, the model obeys the 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 the 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, the Shape Bias can be realized by placing a heavier weight on the attribute about shape as mentioned earlier. We can also realize some kind of context switching mechanism, *i.e.* the Taxonomic Bias by introducing different sets of evaluation functions and weights for each task depending on the Supercategory of the target concept. By the way, the 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 objects (like a car or a cat) in the aspects to be referred by labels. In vocabulary acquisition, it is not an important issue to distinct between such Supercategories, because such distinction is given by perception modules. On the other hand, another issue is more important, which includes the problem of differentiation between 'water and rice', or 'cars and cats'. 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. The flower pot category and the 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 great deal 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 to concepts within the shaped objects' Supercategory. Such knowledge prevents children from selecting into irrelevant attributes during object analysis. When children see a bowl in association 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 touch it with their hands; they may rub it with their dry and/or wet fingers; or they may taste it with their tongues. However, they know that there is no way of locomotion for such a object, so do not try to observe such a attribute. 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 the Mutual Exclusivity Bias, he may interpret a 'terrier' is another name of the object, and may think that the category 'terrier' differs from a 'dog', guided 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 the hierarchical case, since one of them includes the other, it is typical that the newly labeled object already has a first label.

We illustrate 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 newly labeled object is small, the learner would interpret that they are hierarchically related, according to the Principle of Contrast and the Taxonomic Bias. Or, if the similarity is large, he would interpret that they are mutually exclusive based on the Mutual Exclusivity Bias.

These three objects are different with respect to typicality as members of the '`dog`' category. 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 the 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 occurs 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

```
 (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

`animate`, we put 1.5 points per one difference on `shape` dimension than the other `attr` predicates.

In this case, we count that the difference of appearance 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 a 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. [2]

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.

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

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 correspond 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 the concept learning phase, the concept hierarchy serves for identifying the Supercategory which the target object belongs to and therefore selecting 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 a concept hierarchy. One possible trigger to build a 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 show results of experimental learning. At First, we explain the description, which is used for both observation input and category intension.

In the second subsection (subsection 4.2), we show an experimental result where the learner acquires labeled concepts that are in the same domain. The learner is given pets objects and tries to learn basic level nouns ('`dog`' and '`cat`') [3] and their subordinate ones. We regard certain biases appears their effect to suppose inter-concepts relations.

Subsection 4.3 shows difference in important properties to descrive concepts among domains. Descriptors for dining instruments are different in their types comparing to those for pet animals. To find sets of important properties may be useful (1) to guess what kind of domain the newly introduced labels belong to and (2) to suggest new domains under the innate Supercategories.

4.1 Description

Figs. 3 and 4 are the input list representeng one of object. We explain on some piecies in this description.

First, we use four predicates to descript objects. '`tax`' and '`attr`' represent categorical classifier and general attribute (see above), respectively. '`subobj(A, B)`' represents that `A` is a part of an object `B`. `B` itself can be part of another object, so this predicate can be used recursively. '`connection(A, B, C, D)`' represents that part `A` has contact with `C` at the direction `B` from its center; and `C` does with `A` at the direction `D`. Note that predicates '`subobj`' and '`connection`' are auxiliary for represent shape structure of objects, and have no direct effect to hypothesis evaluation.

We should explain some types of general attribute representations. On the line 20 of the list, the third argument have a listed value `[y_axis,`

[3] Nouns are classified into several levels depending on their commonness in cognitive psychology community. Frequently used nouns such as 'cat' or 'dog' are categorized as basic level and those nouns like 'animal' which are more abstract than basic level are categorized as superordinate level. Those which are less abstract are categorized as subordinate level. This classification reflects conceptual hierarchy.

z_axis, x_axis]. This clause represents that the y_axis of the part obj041a is the longest among the three axes. Also, on the line 27, the clause having the third term z_axis/[y_plus, y_minus] expresses that the part obj041b have its posture as the higher at the further and the lower at the nearer from the observer's viewpoint.

This list was manually encoded by observing a piece of photoprint to imitate a real human eye sensor. In the picture, a dog whose breed is 'weimaraner' stands staring at the photographer.

4.2 Learning in a Domain Supposing Concept Hierarchy

In the experiment shown in this subsection, we gave 4 objects, 4 labels and 6 namings. This experimental learning is employed within one domain, which we call mammals' one. Also, the experiment is under the Supercategory 'animate' all the way through.

Objects contains 2 dogs and 2 cats. The observation description on one of these dogs, whose breed is weimaraner, is shown in the previous section. The other dog is a dachshund. Cats include 1 persian and 1 japanese bobtail.

Labels are 'tt dog', 'weimaraner', 'dachshund' and 'cat'. Fig. 5 shows the order of naming.

When we name the weimaraner as 'weimaraner', the learner check that the object already has a name 'dog'. Then the learner judges whether the object should be eliminated from the concept 'dog' or not. If the object seems to be negative for 'dog', the concept needs revision after the induction of 'weimaraner'. This choice is the result of adoption of the Mutual Exclusivity Bias.

To decide whether to adopt it or not, the learner compares shape-related general attributes between the object (Figs. 3 to 4) and the category 'dog'. This processing is based on the Shape Bias. The representation of intension of the category 'dog' is shown in Fig. 6. This weimaraner (obj041) fits the concept when we tie obj041a with A, obj041b with F, obj041c with B, and so on. As a result of the comparison, we need neither to eliminate this object from the concept nor to re-induce the category. Therefore this session ends when the induction of 'weimaraner' is finished.

After all naming shown in Fig. 5 are done, we obtain intensions of 'weimaraner' and 'dachshund', remaining the possibility of hierarchical relations with 'dog' respectively. On the other hand, category 'cat' (shown in Fig. 7) also remains such possibility. None of 2 cat objects are inconsistent with the intension of 'dog'. Examples used in this experiment are not sufficient to show mutual exclusivity based on the Shape Bias. However, no cat object is explained by 'dog' intension, and vise versa. It is possible to find evidence of mutual exclusivity between these 2 categories when more objects are introduced as examples.

4.3 Difference of Important Descriptors between Domains

In this subsection, we add 2 objects and 2 labels over the experiment shown in previous subsection. Objects are a spoon and a fork, and lables are 'spoon' and 'tt fork' naturally. These new learning is under the Supercategory inanimate all the way through. Each induction of these categories is not affected by the other, and is not affected by the animal objects that

```
tax(obj041, animation, animate).
attr(obj041, color, gray).
attr(obj041, covering, fur).  % short hair
subobj(obj041a, obj041).  % trunk
subobj(obj041b, obj041).  % head
subobj(obj041c, obj041).  % right fore leg
subobj(obj041d, obj041).  % left fore leg
subobj(obj041e, obj041).  % right hind leg
subobj(obj041f, obj041).  % left hind leg
connection(obj041a, y_minus_z_plus, obj041b, y_plus_z_minus).
connection(obj041a, x_minus_y_minus_z_minus, obj041c, z_plus).
connection(obj041a, x_minus_y_plus_z_minus, obj041d, z_plus).
connection(obj041a, x_plus_y_minus_z_minus, obj041e, z_plus).
connection(obj041a, x_plus_y_plus_z_minus, obj041f, z_plus).
%
% trunk
attr(obj041a, color, gray).
attr(obj041a, covering, fur).
attr(obj041a, shape, elliptic_cylinder).
attr(obj041a, shape, [y_axis, z_axis, x_axis]).
attr(obj041a, direction, y_axis).
% head
attr(obj041b, color, gray).
attr(obj041b, covering, fur).
attr(obj041b, shape, truncated_cone).
attr(obj041b, direction, y_axis).
attr(obj041b, direction, z_axis/[y_plus, y_minus]).
subobj(obj041b1, obj041b).  % head base
subobj(obj041b2, obj041b).  % right ear
subobj(obj041b3, obj041b).  % left year
subobj(obj041b4, obj041b).  % nose
subobj(obj041b5, obj041b).  % right eye
subobj(obj041b6, obj041b).  % left eye
connection(obj041b1, x_minus_y_plus_z_plus, obj041b2, z_plus).
connection(obj041b1, x_plus_y_plus_z_plus, obj041b3, z_plus).
connection(obj041b1, y_minus_z_minus, obj041b4, y_plus_z_plus).
connection(obj041b1, x_minus, obj041b5, y_plus).
connection(obj041b1, x_plus, obj041b6, y_plus).
% right fore leg
attr(obj041c, color, gray).
attr(obj041c, covering, fur).
attr(obj041c, shape, cylinder).
attr(obj041c, direction, z_axis).
attr(obj041c, location, on/ground).9
% left fore leg
attr(obj041d, color, gray).
attr(obj041d, covering, fur).
attr(obj041d, shape, cylinder).
attr(obj041d, direction, z_axis).
attr(obj041d, location, on/ground).
% right hind leg
attr(obj041e, color, gray).
attr(obj041e, covering, fur).
attr(obj041e, shape, cylinder).
attr(obj041e, direction, z_axis).
attr(obj041e, location, on/ground).
```

Figure 3: The former half of a list representing observation on a weimaraner (obj041)

```
% left hind leg
attr(obj041f, color, gray).
attr(obj041f, covering, fur).
attr(obj041f, shape, cylinder).
attr(obj041f, direction, z_axis).
attr(obj041f, location, on/ground).
%
% head base
attr(obj041b1, color, gray).
attr(obj041b1, covering, fur).
attr(obj041b1, shape, truncated_cone).
attr(obj041b1, direction, y_axis).
attr(obj041b1, direction, z_axis/[y_plus, y_minus]).
% right ear
attr(obj041b2, color, gray).
attr(obj041b2, covering, fur).
attr(obj041b2, shape, fin).
attr(obj041b2, shape, ellipse).
attr(obj041b2, direction, [z_axis, y_axis]).
% left ear
attr(obj041b3, color, gray).
attr(obj041b3, covering, fur).
attr(obj041b3, shape, fin).
attr(obj041b3, shape, ellipse).
attr(obj041b3, direction, [z_axis, y_axis]).
% nose
attr(obj041b4, color, gray).
attr(obj041b4, covering, skin).
% right eye
attr(obj041b5, color, black).
attr(obj041b5, color, white).
attr(obj041b5, color, shining).
attr(obj041b5, shape, sphere).
% left eye
attr(obj041b6, color, black).
attr(obj041b6, color, white).
attr(obj041b6, color, shining).
attr(obj041b6, shape, sphere).
```

Figure 4: The latter half of a list representing observation on a weimaraner (obj041)

1	dog	for	the weimaraner
2	dog	for	the dachshund
3	weimaraner	for	the weimaraner
4	dachshund	for	the dachshund
5	cat	for	the japanese bobtail
6	cat	for	the persian

Figure 5: The order of naming through the experiment

```
labeling(dog, X) :-
        tax(X, animation, animate),
        attr(X, covering, fur),
        connection(C, x_minus_y_plus_z_minus, A, z_plus),
        connection(D, x_plus_y_plus_z_minus, A, z_plus),
        subobj(A, X),
        attr(A, covering, fur),
        attr(A, shape, elliptic_cylinder),
        attr(A, direction, y_axis),
        subobj(B, X),
        attr(B, covering, fur),
        attr(B, shape, cylinder),
        attr(B, direction, z_axis),
        attr(B, location, on/ground),
        subobj(C, X),
        attr(C, covering, fur),
        attr(C, shape, cylinder),
        attr(C, direction, z_axis),
        attr(C, location, on/ground),
        subobj(D, X),
        attr(D, covering, fur),
        attr(D, shape, cylinder),
        attr(D, direction, z_axis),
        attr(D, location, on/ground),
        subobj(E, X),
        attr(E, covering, fur),
        attr(E, shape, cylinder),
        subobj(F, X),
        subobj(F1, F),
        attr(F1, shape, truncated_cone),
        attr(F1, covering, fur),
        subobj(F2, F),
        attr(F2, shape, fin),
        attr(F2, covering, fur),
        subobj(F3, F),
        attr(F3, shape, fin),
        attr(F3, covering, fur).
```

Figure 6: The intension of 'dog', after second naming

```
labeling(cat, X) :-
        tax(X, animation, animate),
        attr(X, covering, fur),
        attr(X, color, white),
        subobj(A, X),
        attr(A, covering, fur),
        attr(A, color, white),
        subobj(B, X),
        attr(B, covering, fur),
        attr(B, color, white),
        subobj(A1, A),
        attr(A1, shape, spheroid),
        attr(A1, covering, fur),
        attr(A1, color, white),
        connection(A1a, y_plus, A1b, y_minus),
        connection(A1a, y_plus, A1c, y_minus),
        subobj(A1a, A1),
        attr(A1a, shape, spheroid),
        attr(A1a, covering, fur),
        attr(A1a, color, white),
        subobj(A1b, A1),
        attr(A1b, shape, sphere),
        attr(A1b, color, beige),
        subobj(A1c, A1),
        attr(A1c, shape, sphere),
        attr(A1c, color, beige),
        subobj(A2, A),
        attr(A2, covering, fur),
        subobj(A3, A),
        attr(A3, covering, fur).
```

Figure 7: The intension of '`cat`', after all naming

```
labeling(spoon, X) :-
        tax(X, animation, inanimate),
        attr(X, shape, constant),
        attr(X, color, having_reflection),
        attr(X, color, shining),
        attr(X, direction, y_axis),
        connection(A, y_minus, B, y_plus),
        subobj(A, X),
        attr(A, shape, oval_semisphere),
        attr(A, shape, [y_axis, x_axis, z_axis]),
        attr(A, shape, x_axis/[y_plus, y_minus]),
        attr(A, direction, y_axis),
        subobj(B, X),
        attr(B, direction, y_axis),
        attr(B, shape, board),
        attr(B, shape, x_axis/[y_plus, y_minus]).
```

Figure 8: The intension of '`spoon`'

are within `animate` Supercategory. Fig. 8 shows full description of '`spoon`' intension.

First, we figure out the feature of animal categories. To find such information, we extract description which devide dogs and cats, *i. e.*, description which appears in one intension but dose not in the other. In intension of '`cat`' (see Fig. 7), the following description is included:

```
.....
connection(A1a, y_plus, A1b, y_minus),
connection(A1a, y_plus, A1c, y_minus),
subobj(A1a, A1),
attr(A1a, shape, spheroid),
attr(A1a, covering, fur),
attr(A1a, color, white),
subobj(A1b, A1),
attr(A1b, shape, sphere),
attr(A1b, color, beige),
subobj(A1c, A1),
attr(A1c, shape, sphere),
attr(A1c, color, beige),
.....
```

Parts `A1b` and `A1c` are eyes of cats. Additionally, 2 lines on the top says that these eyes are attached to the part `A1a`, which represent the head. In this description, in is important that the shape of `A1a` is specialized as `spheroid`. Such description set does not appear in '`dog`'s. There are various cats in the world, but roundness of their head seems to make contrast against dogs.

Dogs and cats seem to have the same structure of four legs for walking, but the shape of head seems to be one of keys to distinction between them.

Now let us turn to observe dining instruments. Distinction between spoons and folks is clearer than pet animals domain. The learner should eliminate their handles from observation focus, then analyse the shape of wider terminal.

A set of important properties to distinguish adjacent categories shows the feature of the domain. Shape of the head is important within quadruped animals; shape of one terminal is important within dining tools. We expect to extract such information from intensions and utilize in order to suggest domain itself. Finding appropriate domains may be effective not only for concept hierarchy building but also further category learning.

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 their learners to construct the concept from a given set of attributes. In other words, they do not provide unnamed completed concepts.

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 both the concept construction and the label extraction.

Finally, we would like to mention the feature of our approach against algorithms employing neural networks, that are under the most popular method. First, our learner deals with background knowledge for incremental learning. Implicit representation such as neural network does not provide basis for such incremental learning. Second, our learner utilizes inter-category similarity measure and category-object similarity measure to judge relationship between categories or to collect appropriate example objects. In neural networks, observations and induced intensions are not described explicitly and therefore such measurements cannot be introduced.

Our approach intends to let the machine learner 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 realizing such strategy.

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 biases such as the Taxonomic Bias, the Shape Bias, the Mutual Exclusive Bias and the Principle of Contrast to reduce the 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 types of knowledge which children have 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 the 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 different attributes sets were needed 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 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 can show that some patterns of description are domain-specific. In our future research, we are planning to adopt further sophisticated similarity measure to improve the performance. Also, when we employ the more example object, the intensional descriptions and domain-specific important patterns may become the more clearly.

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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