Usage-based Structuralization of Relationships between Words

Takashi Hashimoto
Lab. for Information Representation, FRP,
The Institute of Physical and Chemical Research (RIKEN)
2-1, Hirosawa, Wako, Saitama, 351-01, JAPAN
Tel: +81-48-467-9626, Fax: +81-48-462-9881
takashi@irl.riken.go.jp
http://www.bip.riken.go.jp/irl/takashi/

Abstract

The development of structure of relationships between words is studied with a constructive approach by means of artificial agents with grammar systems. The agents try to recognize given sentences in terms of their own grammar. A word's relationship to other words, which represents meanings of the word, is derived by analyzing the word's usage in sentences, and which is calculated via the mutual dependency between words and sentences. The agents differentiate recognized words into clusters in a space of relationships among words. The structures of clusters can be classified into several types. The dynamics of clusters such as merging, boundary expansions, structural changes are observed. These clusters and their dynamics have some relevance with linguistic categorization.

1 Introduction

Language can be seen as an evolutionary system. At the time of its origin, a successful language must consist of simple syntax, a small number of words, and very few abstractions. Human languages have been constructed through such processes as word formation, grammaticalization, or expression diversification. Our own communication has inherited, via evolutionary pathways, some of the features of animal communication [1]. Accordingly, it is important to study the evolutionary aspects of language from primitive communication systems. Even now language is changing. Pidgin and creole languages are increasing in their complexity, and new expressions are daily being added to every language. Language, in short, is an ever-changing system.

Evolutionary linguistics is a new candidate for potentially clarifying the origins and evolution of language [2]. It is important to note that the origins and evolution of language are typically expressed as such dynamically complex systems as emergence, self-organization, collective behavior, clustering, diversification, hierarchy formation, and so on.

A language system must have both adaptability and stability. If a language is too rigid, its users will not be able to formulate new expressions to describe diverse experiences, and if it is too unstable, no communication will be possible at all. Geeraerts [3] explains this point as it pertains to categorization: "To prevent the categorical system from becoming chaotic, it should have a built-in tendency towards structural stability, but this stability should not become rigidity, lest the system stops being able to adapt itself to the ever-changing circumstances of the outside world." Such dynamical stability and adaptability is often seen also in complex systems.

Constructive approaches are highly advantageous for understanding dynamically complex systems [4]. These approaches are also useful for studying evolutionary linguistics, because they are based on the notion that language is an emergent phenomena in interacting distributed agents. In contrast to conventional linguistics, which attempt to describe various language phenomena, the constructive approach builds models with elements having its own internal dynamics and interaction among them, and observe emergence of global order as language-like behavior. We insist, however, that only emergence of global order is not enough. Since language is an ever-changing system, models must show not only emergence but the dynamics of global order through the dynamics between elements. Perhaps the most important consideration in the modeling of evolutionary language system is the introduction of the dynamics of elements. Elements can change their internal states and their relationships to other elements. These underlying dynamics often model the dynamics of the global-level relationships.

In keeping with this approach, we previously presented a language game played between number of agents having different grammar systems [5, 6]. We found that evolution of syntactic structure and emergence of community sharing common usages of language. The common usages punctually change through evolution of individual grammars. In the present paper, we incorporate a word meaning feature, the relationships among words, into the above work, and tracing the development of this feature so as to understand the development of meaning structures of language.

One of the most controversial problem in linguistics is defining the meanings of words. A lot of discussion has been devoted to this problem. For example, words can be taken as indicators of external objects; they can be represented by bundles of necessary and sufficient conditions; they can be done by vectors of several features [7]; they can be done by set of binary features. We insist that the meanings of words can best be represented by their interrelationships, as Cruse [8] has written, "We can picture the meaning of a word as a pattern of affinities and disaffinities with all the other words in the language with which it is capable of contracting semantic relations in grammatical context."

The meanings of words should thus be discussed in terms of how language is used [9]. In the present context, this means that a word's relation to other words should be derived by analyzing the word's usage in numerous sentences. It is often said that a word indicates (a class of) objects. For example, the word *cup* indicates an object, cup. However, from a usage-based viewpoint, we rather consider the whole sentence "A word *cup* indicates an object, cup" as one usage of the word itself. This sentence forms a part of the web of interrelationships of the word *cup*, with the words such as *object* or *indicates*.

Relations between words can be characterized as either syntagmatic and paradigmatic. The syntagmatic relation is established by the association of words in a sentence: for instance, by the relation between the words *read* and *book* in the sentence *I read a book*. The paradigmatic relation represents a semantic similarity between two grammatically identical words: for instance, the relation between the words *book* and *magazine* in the sentences *I read a book* and *I read a magazine*. Paradigmatic relations can be grasped through syntagmatic relations. In the above examples, the sentence *I read a book* suggests the syntagmatic relation between the words *read* and *book* and the sentence *I read a magazine* do the syntagmatic relation between *read* and *magazine*. Through the basis of their relations with the word *read*, the words *book* and *magazine* can also be related.

We evaluate such interrelationships by gauging a word's similarity to all other words based on its usage in sentences. Similarity is an important concept with respect to categorization. Entities are categorized via their similarity with each other. Similarity is a graded and subjective notion. To calculate the similarity of words based on their usage in sentences, we adopt Karov and Edelman's algorithm [10], which allows for the similarities to be graded. Karov and Edelman stress the mutual dependency between words and sentences, i.e., similar words are used in similar sentences and similar sentences are composed of similar words.

The rest of this paper is organized as follows. At first, we define an artificial agent with grammar systems and its modification instructions as well as the calculation algorithm of similarity among words. After showing the basic characteristics of the similarity formula, simulation results of agents with grammar modification are shown, which are a classification of structures according to their word similarities, as well as a developmental pathway for the structures. Finally, we discuss relevance of the structures of word similarities and their dynamics with linguistic categorization.

2 Model

In this section we describe our model. We first define agents as grammar systems, then detail their sentence-recognition process. Next, we define a method of articulating a sequence of words in a *sentence*, that is a sequence of the symbols '0' and '1'. Next, the similarities among words are defined. Finely, instructions for modifying a grammar system are given.

2.1 Agent

An agent is defined as a grammar system,

$$G_i = (V_\mathrm{N}, V_\mathrm{T}, F_i, S), \tag{1}$$

where V_N is a set of non-terminal symbols, V_T is a set of terminal symbols, F_i is a list of rewriting rules, S is a start symbol, and a suffix i is ID of an agent. In this paper we use $V_\mathrm{N} = \{S, A, B\}$, $V_\mathrm{T} = \{0, 1\}$ as non-terminal and terminal symbols, respectively. A rewriting rule is an ordered pair (α, β) which is written as $\alpha \to \beta$. Here, α is a symbol over V_N. And β is an arbitrary finite string of symbols over $V_N \cup V_T$ not including the same symbol with α. The type of grammar that an agent can have is a context-free or regular grammar here.

2.2 Recognition of Sentences

Agents that are defined as grammar systems try to speak and recognize sentences. During the recognition process, an agent tries to rewrite from a given sentence into the start symbol S by use of its own grammar. The sentence is checked against each rule in the rule list, beginning with the topmost rule, to determine whether it contains the element in the right hand side of each rule. If it does, then the leftmost sequence that is equivalent to the right hand side is rewritten as the left hand side of the rule. If the agent has no applicable rule even if the rewritten sentence is not S, the rewritten sentence is put back one step and the searching and rewriting processes restart from the next rule of the applied rule in the agent's rule list. This process is recursively applied. If an agent can put a given sentence back to the symbol S within 500 rewriting steps, we say that the agent can recognize the sentence.

2.3 Articulation

We introduce a method of articulating a sequence of words in a sentence based on the parsing of that sentence. Agents have three types of rewriting rules:

$$N \rightarrow \text{sequence of } T\text{s}, \tag{2}$$

$$N \rightarrow \text{sequence of } N\text{s}, \tag{3}$$

$$N \rightarrow \text{sequence of } N\text{s and } T\text{s}, \tag{4}$$

where N and T are a non-terminal and a terminal symbol, respectively. A *word* is a series of terminal symbols in Eqs. (2) and (4). A sentence is a sequence of terminal symbols. Each agent articulates sequences of words within sentences by parsing it.

For example, an agent with a rewriting rule list, $S \rightarrow A0B, A \rightarrow 10, B \rightarrow 11$, parses a sentence "10011" as

$$10011 \overset{A \leftarrow 10}{\Longrightarrow} A011 \overset{B \leftarrow 11}{\Longrightarrow} A0B \overset{S \leftarrow A0B}{\Longrightarrow} S$$

and articulates it as a sequence of words "10·0·11". A mark '·' is used for a separator between words. The parsing tree is depicted in Fig. 1(a).

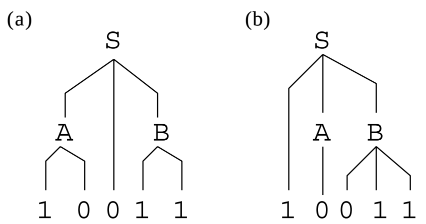


Figure 1: Two examples of a parsing tree.

The way of articulation of a given sentence depends on the rule list, which expresses the subjective aspect of similarity among words. The sentence in the above example, "10011," will be broken down into the word sequence "1·0·011" by an agent with the rewriting rule list, $S \rightarrow 1AB, A \rightarrow 0, B \rightarrow 011$, through the recognition process,

$$10011 \overset{A \leftarrow 0}{\Longrightarrow} 1A011 \overset{B \leftarrow 011}{\Longrightarrow} 1AB \overset{S \leftarrow 1AB}{\Longrightarrow} S,$$

the parsing tree of which is shown in Fig. 1(b).

2.4 Similarity and Affinity

Relationships between words are defined by the similarity of their usage in sentences. We use Karov and Edelman's definition [10] with some revisions. A key concept in this definition is the mutual dependency between words and sentences. That is, similar words appear in similar sentences and similar sentences are composed of similar words. We call a space of the relationship among words *word-space*.

The similarities between words and between sentences are respectively defined by the following formulae:

$$sim_{n+1}(w_i, w_j) = \begin{cases} \sum_{s \ni w_i} weight(s, w_i) aff_n(s, w_j) & \text{if } i \neq j \ , \\ 1.0 & \text{if } i = j \ , \end{cases} \tag{5}$$

and

$$sim_{n+1}(s_i, s_j) = \begin{cases} \sum_{w \in s_i} weight(w, s_i) aff_n(w, s_j) & \text{if } i \neq j \ , \\ 1.0 & \text{if } i = j \ . \end{cases} \tag{6}$$

The functions $aff_n(s, w)$ and $aff_n(w, s)$ represent the affinity of a word for a sentence and that of a sentence for a word, respectively. They are defined as

$$aff_n(s, w) = \sum_{s' \ni w} weight(s', w) sim_n(s, s') \ , \tag{7}$$

$$aff_n(w, s) = \sum_{w' \in s} weight(w', s) sim_n(w, w') \ . \tag{8}$$

In the above four formulae, a suffix n indicates number of times to iterate, $w \in s$ means words included in a sentence s, and $s \ni w$ means sentences including a word w. The functions $weight(s, w)$ and $weight(w, s)$ are normalizing factors that decide what contribution each word and sentence will make toward affinity and similarity. They are given by

$$weight(s, w) = \frac{factor(s, w)}{\sum_{s' \ni w} factor(s', w)} \ , \tag{9}$$

$$factor(s, w) = \frac{p(s)}{\#(s, w)} \ , \tag{10}$$

$$weight(w, s) = \frac{factor(w, s)}{\sum_{w' \in s} factor(w', s)} \ , \tag{11}$$

and

$$factor(w, s) = \frac{1}{p(w) lg(s)} \ . \tag{12}$$

In Eqs. (10) and (12), $p(w)$ and $p(s)$ are the appearance frequencies of a word w and a sentence s, respectively; $lg(s)$ is the length of a sentence s, which is defined by the number of words included in the sentence; and $\#(s, w)$ is the number of appearances of a sentence s including a word w. The more a word is used, the less informative it is, but the more a sentence is used, the greater its contribution. A word in a longer sentence is less important than one in a shorter sentence. If a word is absent in many sentences, its effect on similarity and affinity will be greater than that of ubiquitous used words.

At the initial iteration step ($n = 0$), the diagonal part of word similarity ($sim_0(w_i, w_i)$) is 1.0; the others are 0.0. Word-sentence affinity (Eq. (8)) at $n = 0$ is calculated from this initial word similarity matrix. Then, these four formulae are iteratively calculated as Eqs. (6) $\rightarrow$ (7) $\rightarrow$ (5) $\rightarrow$ (8).

2.5 Modification of Grammar

The grammar of an agent is modified in the course of time, depending on the usage at recognition processes. Modifications of the rule list are defined by the following three processes:

adding modification An altered rule of the mostly used rule at recognition processes is added to the end of the rule list.

replacing modification A randomly selected rule from the whole rule list is replaced with an altered rule.

deleting modification The least used rule is deleted from the rule list.

The times of use of each rule are counted only upon successful recognition of a path. Rules which are rewritten to erroneous recognition paths are not regarded as being used. These modifications are applied in probabilities $m_{\rm add}$, $m_{\rm rep}$, and $m_{\rm del}$, respectively.

The ways of altering of a rule are as follows: 1) Replace a symbol of the left-hand of the rule with another non-terminal symbol. 2) Replace a symbol in the right-hand of the rule with another non-terminal or terminal symbol. 3) Insert a symbol in the right-hand side of the rule. 4) Delete a symbol from the right-hand of the rule. One of these alterations, as well as the point of insertion, replacement, or deletion in a rule, is randomly determined.

3 Characteristics of Word Similarity

We shall begin the analysis of our system with a consideration of the characteristics of word similarity. Similarity, straightforwardly understood from the definition, has the following properties: Word similarity with the word itself is always 1.0; A word has higher similarity with a word in a frequent sentence than with one in a rare sentence; It has higher similarity with a word in a short sentence than with one in a long sentence; It has lower similarity with a word which is used with a frequent word in a sentence than with a word which is used with a rare word.

Words, even if they are not used in a sentence, can have similarity through their relation with other words.

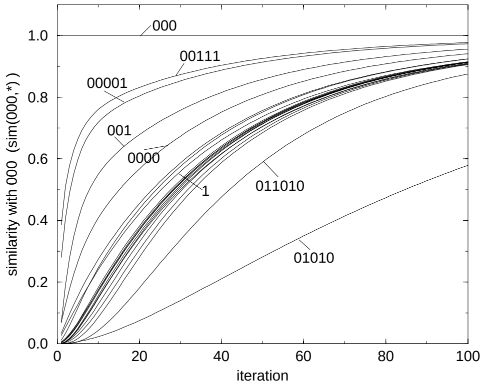


Figure 2: An example of transition of word similarity in the course of iteration. The graph is the similarity of a word '000' with the other words per iteration of calculation of similarity and affinity. Iteration step vs. word similarity of a word '000' with the other words.

By a sentence "$w_1 \cdot w_2$," the word w_1 has similarity with the word w_2. Another sentence, "$w_2 \cdot w_3$," is the case for the similarity between the words w_2 and w_3. Despite the fact that no sentence uses w_1 and w_3 simultaneously, these two words come to have similarity through w_2 by iteration of the calculation algorithm. If the words have similar way of use within sentences, they are regarded as highly similar. With this feature of the algorithm we can take the paradigmatic relations between words into consideration.

If the weight functions, Eqs. (9) and (11), do not change in the course of iteration, both word similarity and sentence similarity are non-decreasing functions of the iteration number n. Therefore, similarity converges to 1.0 after all.

The above characteristics are clearly seen in the following simulation, in which the grammar of agents is not modified in the course of simulation. Randomly generated sentences, in which the maximum number of symbols in a sentence is restricted to 8, are given to an agent until it recognizes 100 sentences. The similarity between all word-pairs is calculated after recognitions of 100 sentences. Since the appearance frequencies of each word and each sentence are fixed after all recognitions, the weight functions do not change in the calculation.

An example of word similarity change per iteration is shown in Fig. 2 for a word '000'.[1] We can see monotonically increasing curves of similarity, which will converge to 1.0. Similarity with the word itself, indicated by '000', is always 1.0 by definition. Similarities with words

[1] The rule list of the agent in this example is copied from a agent evolved in a simulation of our previous work [5, 6].

'00111' and '00001' rapidly increase in early iteration steps. Because these words are used in two-word sentences with the word '000' as "000·00111" (3 times) and "000·00001" (2 times), respectively, they have direct and strong relations. The difference between $sim(000, 00111)$ and $sim(000, 00001)$ depends on the times to be used. A word '0000' is used in a three-word sentence "000·0000·1" (2 times). Therefore the word '0000' has high similarity with '000'. In spite of the use of '1' in the same sentence, the word has less similarity with '000' than similarity between the words '000' and '0000'. This is because the word '1' is used many more times (79 times) than the word '0000' (9 times).

Resemblance of usage of words in different sentences gives a high similarity value even when the words are not used in a sentence, as can be seen in the similarity between '000' and '001'. The word '001', which is not used with '000' in any sentence, is used only in sentences "001·00111," "001·00001" and "001·0000·1." But the respective usages of the words '000' and '001' resemble each other in these and the above listed sentences. Therefore $sim(000, 001)$ is a rather high value (Fig. 2).

4 Results of Simulation with Modification of Grammar

We describe the results of simulation with the rule modification processes which are introduced in §2.5. Sentences of at most 8 symbols are given to some agents. Similarity is calculated when the agent recognizes a given sentence. Thus the iteration step coincides with the number of recognized sentences. The modification occurs every 10 given sentences. Probabilities for rule modifications are $m_{\mathrm{add}} = m_{\mathrm{rep}} = m_{\mathrm{del}} = 0.3$.

4.1 Dynamics of Word Similarity

Since similarity is calculated dynamically, the weight functions are not fixed in the course of iteration. Figure 3 is an example of transition of word similarity per each recognition. The initial rule list is the same as that for the agent depicted in the previous section.

In this case, the similarity functions are not non-decreasing. We can see more complex dynamics than that of without modification of grammar. Similarity with new words climbs from 0.0, while similarities with already appeared words are pulled down by the effect of the new words. Some words form clusters, as described in the next subsection. Similarities with words in a cluster show synchronized transitions.

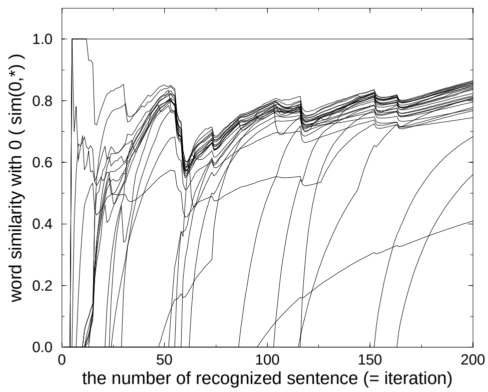


Figure 3: An example of transition of word similarity per each recognition from a simulation with the grammar modifications. In this simulation, similarity is calculated per each recognition. Therefore the scale of horizontal axis coincides with the number of iteration. Rule list is modified per 10 given sentences. The initial rule list is the same as that in the example in the previous section. The similarity of a word '0' with other words is shown. X-axis is the number of recognized sentences (= iteration step), and Y-axis is the word similarity.

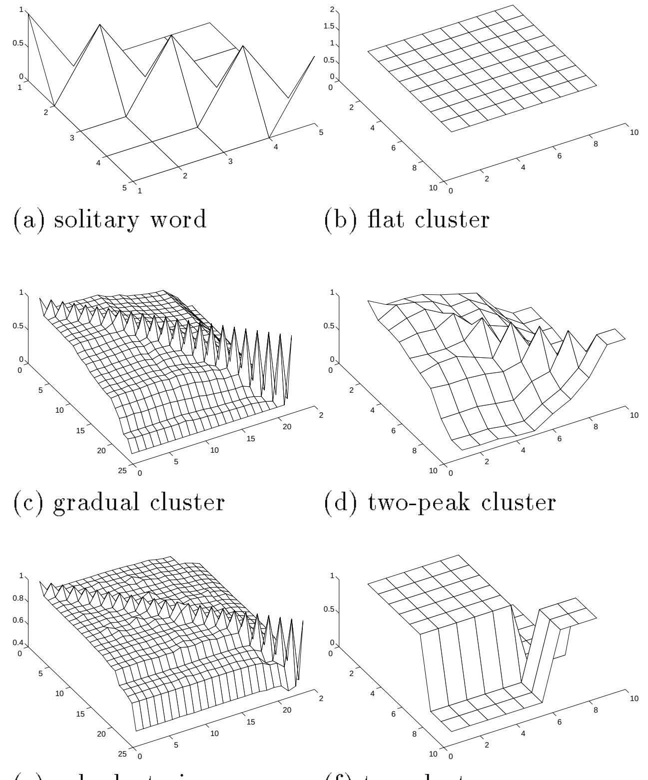
4.2 Classification of Structure in Word-space

Words are clustered in word-space, the space of word similarity, according to having or not having similarity with each other. Various shapes of structures of cluster appear in the course of simulations. Their variety depends on the initial grammar of the agents. We classify structures in word-space into six types according to their shapes. Examples of simple structures of each type are shown in Fig. 4. Structures in word-space in actual simulations are compositions of some of these types.

The features of these graphs can be summarized by one of the following. (a) A word has no relation to other words; we call such word a solitary word. (b) Words in a cluster have almost identical similarities with each other; we term this cluster a flat cluster. (c) Words form a cluster. Similarity between words in the cluster depends on words and gradually changes; we term this a gradual cluster. (d) Words are in a cluster but there are two peaks of similarity. Similarity from a word decays along one side but climbs along the opposite side; we term this a two-peak cluster. (e) There is a cluster having a stepwise structure. Words are thought to be divided in sub-clusters. (f) Words form plural, unrelated clusters.

4.3 Dynamics of Structure in Word-space

A general scenario of the development of structure in word-space is the following. At first an agent can recognize only a one-word sentence. It then develops the ability to recognize several sentences, but these all are one-word sentences, and therefore there are several solitary



(a) solitary word (b) flat cluster

(c) gradual cluster (d) two-peak cluster

(e) sub-clustering (f) two clusters

Figure 4: Examples of structures in word-space. Z-axis is word similarity defined by Eq. (5). Words are aligned in X- and Y- axes in descending order from a standard word appropriately selected to smoothly change similarities. We have six distinct types of structures. (a) Solitary word. A word has no similarity with the others. (b) Flat cluster. All words have almost identical similarity with the all other words in the cluster. In these two cases, (a) and (b), the shape of clusters does not depend on the order of words in the X- and Y- axes. (c) Gradual cluster. Words are arranged in the X-axis in descending order of similarity with a standard word. In this case: '0' (standard word), '1', '11', $\cdots$, '111'. In case of gradual cluster, similarities of words with the last word in X-axis, '111', are also descent order. (d) Two-peak cluster. Words are arranged in the same manner as in (c). In this example: '11' (standard word), '0', $\cdots$, '0010'. In contrast with the gradual cluster, similarities of words with the last word in X-axis, '0010', are ascending order. (e) Sub-clustering. Words are again arranged in the same manner. In this example, '0' (standard word), '0000', $\cdots$, '00000'. Words are divided into two groups which have almost the same value of similarity with words in the same group. (f) Two clusters. There are two independent clusters in word-space.

words in word-space. Then it becomes able to articulate sentences into plural words, which forms relations between words. Eventually words form gradual clusters in word-space. Such clusters change their structure through such processes as expansion of boundary or mergence of two clusters. Parallel to this development in word-space, the syntactic structure also develops from sequential, to branch, and then, to loop structures.

Let us examine this scenario thoroughly by the example of two simulations. One is a simulation from the simplest grammar, namely from only one rewriting rule, which will show the developmental path in the early stage. The other is from a large grammar and will illustrate structural change in clusters.

4.3.1 Development in Early Stage

A simulation which is started from an agent with only one rule as the initial grammar is taken to illustrate the development in word-space at the early stage. We will be able to see a typical pathway of development where sentences make relations between some solitary words and expand boundaries of clusters.[2]

An agent whose initial grammar has only a rule $S \rightarrow 1$ hears randomly generated sentences and tries to recognize them. Grammar of the agent changes in the course of simulation according to the modification method of grammar defined in §2.5.

Figure 5 shows increases in the whole number of recognized sentences, indicated by 'whole' in the graph and denoted N_r, and in the number of distinct sentences, indicated by 'distinct' in the graph and denoted N_k.

We depict the developmental pathways of structures in word-space by showing some snapshot figures of word-space in Fig. 6. Words articulated from recognized sentences are aligned as '0', '1', '01', '101', '10', '11', '011', '00' from 1 to 8 on the X and Y axes to clearly show structural changes in word-space.

The first sentence the agent can recognize is "1", and it is a one-word sentence. The shape in word-space is the simplest structure as Fig. 6(a), a solitary word structure classified in §4.2.

Since all sentences, which appear until N_g is 1580, namely "0","1", "01", "101", and "10", are recognized as one-word sentences, there are only solitary words in word-space (Fig. 6(b)).

From N_g of around 1580 to 1900, N_r of the agent is on a rapid increase phase as in Fig. 5. This phase begins when the agent gets an effective loop structure in its grammar. A set of recognizable sentences is enlarged by

[2] We should say it is an atypical example of simulation starting from small grammar. In case that the initial grammar is quite small, it is hard to develop to be able to recognize enough sentences to show particular structure in word-space. Since the modification ways introduced in §2.5 are rather weak in order to enlarge the set of recognizable sentences.

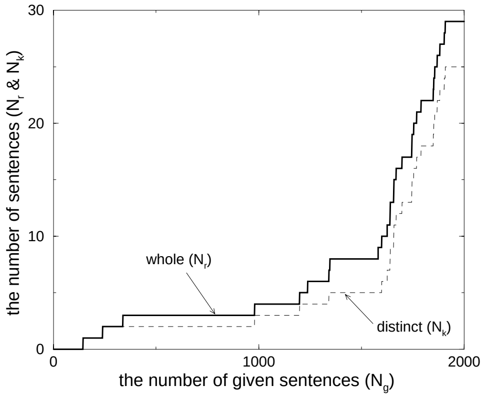


Figure 5: Transitions of the number of whole (N_r) and distinct (N_k) sentences which are recognized by an agent per each given sentence. The solid and dashed lines are the whole and distinct number of sentences recognized by an agent, respectively.

this loop structure. The fact that N_k also grows almost parallel to the line of N_r implies that the agent recognizes many new sentences.

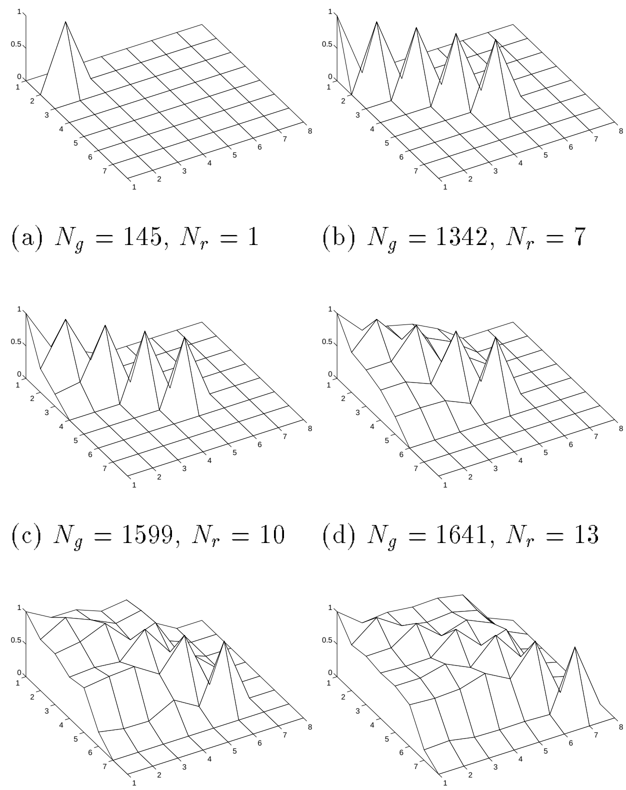
In this rapid increase phase, many of the new sentences are no more than one-word in length. They make connections between solitary words. For example, a sentence “000111” first recognized at $N_g = 1599$ is articulated to “0·0·01·1·1”. By this sentence solitary words ’0’, ’1’, and ’01’ are related and these three words form a gradual cluster (Fig. 6(c)). By the next recognized sentence, “0·0·101·1·1·1”, a word ’101’ is incorporated into this cluster. As this manner, all five of the solitary words are related by $N_g = 1641$ (Fig. 6(d)).

The boundary of the cluster is extended through recognition of new sentences. A new word ’11’ is incorporated into the cluster at $N_g = 1747$ by a sentence “0·101·11” (Fig. 6(e)) . At $N_g = 2853$ a sentence “0·0·0·1·011·1” expands the boundary to a new word ’011’ (Fig. 6(f)).

4.3.2 Development from Large Grammar

In this subsection, we exemplify a developmental path from an agent with many rules in its grammar. If an agent has the ability to recognize sentences to some extent at the initial point, it is likely to develop some structure in word-space. We will show a merging process of clusters, a structural change from plural peak to nearly flat cluster, and a boundary expansion.

The agent in the following example, the same as that used in §3, has 33 rules in its initial grammar. We would like to focus attention on a scenario of structural change in word-space. In the early period, there are two clusters and a solitary word (Fig. 7(a)). One cluster has a ragged surface and the other has a flat one. At $N_g = 74$, the former cluster develops two peaks. The latter expands its boundary and also becomes a two-peak cluster (Fig. 7(b)).



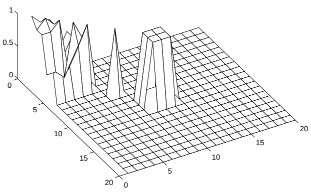
(a) $N_g = 145$, $N_r = 1$ (b) $N_g = 1342$, $N_r = 7$

(c) $N_g = 1599$, $N_r = 10$ (d) $N_g = 1641$, $N_r = 13$

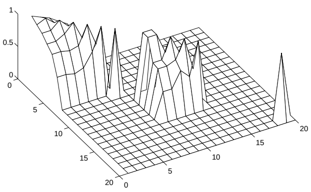
(e) $N_g = 1747$, $N_r = 19$ (f) $N_g = 1853$, $N_r = 24$

Figure 6: The developmental path of structures in word-space of an agent from one rule as the initial grammar is shown. Z-axis is word similarity. Words are arranged in XY-plane to clearly show the clustering and its dynamics in word-space. That is, ’0’, ’1’, ’01’, ’101’, ’10’, ’11’, ’011’, ’00’ from 1 to 8. The symbols N_g and N_r in the equations under each graph are the number of given and recognized sentences, respectively.

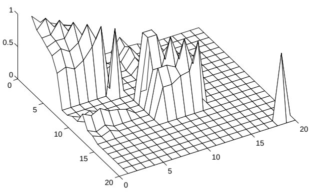
We can see a merging process of three clusters into a flat cluster through the three-peak structure in Fig. 7(b) $\sim$ (f). A sentence “00·0101·1” makes a connection between two clusters mentioned above (Fig. 7(c)). This sentence does not contain a new word, but the usage of words in this sentence is quite new. The solitary word is included in the first cluster, and the three clusters begin to have stronger relations through more sentences (Fig. 7(d)). The connected cluster changes into a three-peak shape (Fig. 7(e)). But this three-peak



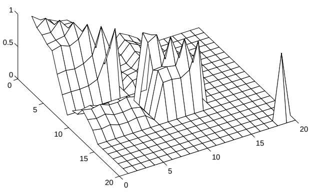
(a) $N_g = 30,\ N_r = 5$



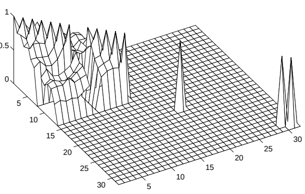
(b) $N_g = 74,\ N_r = 10$



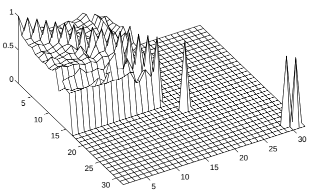
(c) $N_g = 85,\ N_r = 11$



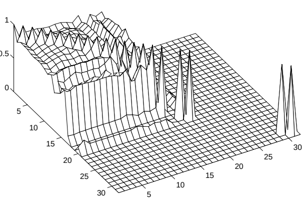
(d) $N_g = 120,\ N_r = 15$



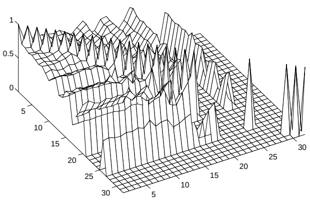
(e) $N_g = 161,\ N_r = 20$



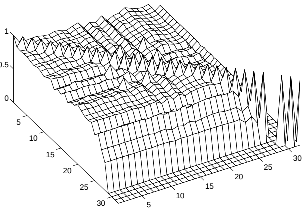
(f) $N_g = 308,\ N_r = 40$



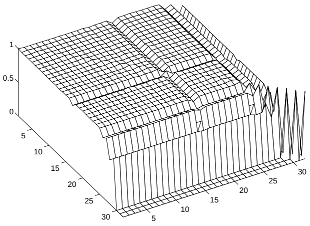
(g) $N_g = 427,\ N_r = 53$



(h) $N_g = 500,\ N_r = 70$



(i) $N_g = 938,\ N_r = 200$



(j) $N_g = 1911,\ N_r = 700$

Figure 7: The developmental path of structures in word-space is shown. Z-axis is word similarity. Words are arranged in XY-plane to clearly show clustering and its dynamics in word-space. The symbols N_g and N_r in the equations under each graph are the number of recognized and given sentences, respectively.

structure does not endure for long before turning into a nearly flat cluster structure with an expanding boundary (Fig. 7(f)).

By recognizing new sentences, the cluster gets bigger and incorporates more solitary words (Fig. 7(g) and (h)). The similarity among old words loses its raggedness, but the new words have a smaller similarity at its boundary (Fig. 7(i)).

In the period of $N_g = 1680 \sim 1940$, the agent can recognize almost all words. This is because, by this time, the agent has one of the following two rule sets in its grammar:

$$S \rightarrow 0, A \rightarrow 1, A \rightarrow B, B \rightarrow S, S \rightarrow AA,$$

or

$$S \rightarrow 0, A \rightarrow 1, S \rightarrow AA, A \rightarrow S.$$

By this set of rules, all sentences except for a sentence "1" can be recognized. All sentences are broken to combinations of the words '0' and '1' by this grammar, therefore no new word appears during this period. Consequently, the boundary of the cluster no longer expands, and the similarity among almost all words in the cluster finally approaches 1.0, which is the reflex of the convergence nature noted in §3, and which makes the structure of the cluster nearly flat, as in Fig. 7(j).

5 Discussion

5.1 Clustering as Categorization

We have shown clustering structures in §4. This clustering can be regarded as categorization of words by the agent, since words in a cluster have stronger relation with each other and less relations with words out of the cluster. Let us devote a little more space to discussing each types of structure classified in §4.2 from this point of view.

A solitary word is a word without any similarity to other words (Fig. 4(a)). Strictly speaking, we cannot say it is a cluster and also a category. Actually, we do not have a category with only one member in our knowledge system. There might be, however, such a simple structure of knowledge at the very beginning of our development.

All words in a flat cluster structure have almost identical similarity (Fig. 4(b)). Since its boundary is sharp, it is clear whether an entity is a member of the cluster or not. This type of cluster is like a category in which members are rigidly determined by *necessary and sufficient conditions* as scientific notions.

In contrast to the flat cluster, a gradual cluster has a graded change in similarity from large to small (Fig. 4(c)). This cluster has a peak. If we think of it as a category, a peak corresponds to the central member of the category. Words having small similarity with the central one are peripheral members of the category. This structure is like a *prototype category* [11, 12]. To what extent words are included in the category is matter of gradient.

The two-peak cluster (Fig. 4(d)) is an analogue of a category with two central members. It can be regarded as a *polysemous category*. All words in a single peak structure are characterized by how similar they are to a central member in the category. Whereas in the plural peak structure, such as in the case of two peaks, there are words which are similar to one central member but not to the other one, and there are words which have some degree of similarity to both central members of a category.

We can see the sub-clustering structure into two groups of words in a cluster (Fig. 4(e)). One is words with high similarity and the other is words with rather lower similarity. The two groups can be regarded as two sub-categories within the category. This is the simplest case of a hierarchy of categories.

The structures of categories should change through various experiences. In our model, we have seen dynamics of clusters in word-space in §4.3.1 and §4.3.2. These dynamics are the expansion of boundaries, the establishing of connections between clusters, the incorporation of solitary words, and the structural changes from gradual or two-peak to flat cluster.

In the case of boundary expansions of clusters as in Fig. 6(d) $\sim$ (f) and Fig. 7(f) $\sim$ (i), the structure of the original clusters does not undergo large change. This satisfies the requirements for adaptability and stability of categorical system noted in §1 and shows resemblance, also in the context of dynamics, to the prototype category in its feature of flexibility, as expressed by Taylar [12] when he says: "Prototype categories have a flexibility $\cdots$ in being able to accommodate new, hitherto unfamiliar data. $\cdots$ New entries and new experiences can be readily associated, perhaps as peripheral members, to a prototype category, without necessarily causing any fundamental restructuring of the category system."

What, then, is the correspondence with a sentence which makes a connection between clusters as shown in Fig. 7(c)? One candidate is a metaphorical expression. A metaphor connects two semantic domains. For example, in the sentence *Sally is a block of ice*, the domains of the human and nonhuman or of the animate and inanimate entities are connected.

But we cannot insist on this correspondence so strongly. Metaphor is not the only connection between two domains, but the basic logic of an original domain is applied to a destination domain by metaphor. Usually, the original domain is concrete and easy to conceptualize; on the other hand, the destination is abstract and hard to conceptualize [13]. But in our case, the two clusters are merely related, and we can discuss neither the mapping of logic between two categories nor which is abstract or concrete.

5.2 Future Problems

We plan to extend our model to a communication network system to discuss the emergence of a social structure among agents. In addition to this extension, we hope to address the following problems.

5.2.1 Convergence Nature of Word Similarity

The similarity among words and that of sentences by our definition has a non-decreasing nature. Therefore, by static calculation the similarities finally converges to 1.0, as shown in §3. This nature appears even in the dynamical calculation in §4, and structures in word-space tend to approach nearly flat clusters. This is partly because the set of vocabulary and symbols in our model is much smaller than that in an actual language system. To avoid this convergence, we should set some restrictions to calculate similarity.

5.2.2 Language Externals

We can show the dynamics of categorization and discuss the correspondences of our results with notion of prototype category, e.g., peaks in a cluster with prototypes and the boundary expansions with flexibility of categories. These correspondences will provide a clue to study the dynamics of categorization. But in order to investigate the problem more deeply, especially with respect to the prototype category, we should take into consideration not only interactions with other agent and entities within embedded environments but also interactions of the ability of language use with other cognitive and motor competence.

Our model might be highly structuralistic to talk over such cognitive linguistic notion as the prototype category. There is no external world of agent in our system and similarity and categorization are discussed based on language internal relations. Cognitive linguists say that effects from the language externals are important to the prototype categorization, as Taylor [12] explains: "Prototype effects $\cdots$ arise from an interaction of core meaning with non-linguistic factors like perception and world knowledge, and can thus be assigned to other components of the mind." How we incorporate such language external systems into our model is the next important problem.

6 Conclusion

We have proposed an evaluation of meaning representation by relationship among words based on the relative similarity of language usages, and we have introduced a definition of similarity among words. We studied the development of structure in word similarity space in an artificial agent with a grammar system. Structures of cluster in word similarity space were classified into six groups: solitary word, flat cluster, gradual cluster, two-peak cluster, sub-clustering structure and plural clusters. The dynamics of the structures were found to consist of association of solitary words, boundary expansions, mergence of clusters, and structural change from gradual or two-peak cluster into flat structure. The relevance of these clustering and their dynamics with linguistic categorization was suggested.

Acknowledgment

This work is supported by the Special Postdoctoral Researchers Program at RIKEN. I am grateful to Associate Prof. Takashi Ikegami for his helpful comments and the encouragement. I would like to thank Prof. Shun-ichi Amari for his continual encouragement.

References

[1] Hauser, M. D., (1996), *The evolution of communication*, The MIT Press, Cambridge, MA

[2] Steels, L., (1997), Synthesising the origins of language and meaning using co-evolution, self-organisation and level formation, in *Evolution of Human Language*, Hurford, J (ed.), Edinburgh Univ. Press, Edinburgh

[3] Geeraerts, D., (1985), Cognitive restrictions on the structure of semantic change, in *Historical Semantics*, Fisiak, J (ed.), Mouton de Gruyter, Berlin, 127–153

[4] Kaneko, K. and Tsuda, I., (1994), Constructive complexity and artificial reality: an introduction, *Physica*, **D75**, 1–10

[5] Hashimoto, T. and Ikegami, T., (1995), Evolution of Symbolic Grammar Systems, *Advances in Artificial Life*, F. Morán et al. (eds.), Springer, Belrin, 812–823

[6] Hashimoto, T. and Ikegami, T., (1996), Emergence of net-grammar in communicating agents, *BioSystems*, **38**,1–14

[7] Putnam, H., (1975), The meaning of 'meaning', in *Mind, language and reality*, Cambridge University Press, New York, NY

[8] Cruse, D. A., (1986), *Lexical Semantics*, Cambridge University Press, Cambridge

[9] Wittgenstein, L., (1953), *Philosophische Untersuchungen*, Basil Blackwell

[10] Karov, Y. and Edelman, S., (1996), Similarity-based word sense disambiguation, Technical Report of Weizmann Institute, CS-TR 96-06

[11] Lakoff, G., (1987), *Women, Fire, and Dangerous Things*, Chicago , The University of Chicago Press

[12] Taylor, J. R., (1995), *Linguistic Categorization – Prototypes in Linguistic Theory*, Oxford, Oxford University Press

[13] Lakoff, G and Johnson, M., (1980), *Metaphors We Live By*, Chicago, The University of Chicago Press