Simulation of Language Evolution based on Actual Diachronic Change Extracted from Legal Terminology

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Abstract: Simulation studies have played an important role in language evolution. Although a variety of methodologies have been proposed so far, they are typically too abstract to recognize that their learning mechanisms properly reflect actual ones. One reason comes from the lack of empirical data recorded for a long period with explicit description. Our purpose in this paper is to show simulation models adapt to actual language change. As empirical diachronic data, we focus on a statutory corpus. In general, statutes define important legal terms with explanatory sentences, which are also revised by amendment. We proposed an iterated learning model, in which an infant agent learns grammar through his/her parent's utterances about legal terms and their semantic relations, and the infant becomes a parent in the next generation. The key issue is that the learning situation about legal terms and their relations can be changed due to amendment. Our experimental result showed that infant agents succeeded to acquire compositional grammar despite irregular changes in their learning situation.

1 INTRODUCTION

A goal of the study on language evolution, or evolutionary linguistics, is to explain the origins of the structure found in language (Hurford, 2002). This study has been increasingly interdisciplinary, involving collaborations between linguists, philosophers, biologists, cognitive scientists, robotics, mathematical and computational modelers (Lyon et al., 2007). In particular, simulation studies have played an important role in the field of language evolution. A very important function of simulation is to prove whether a prediction actually and consistently derives from a theory (Cangelosi and Parisi, 2002).

Although a variety of methodologies have been proposed so far (Briscoe, 2002), they are typically too abstract to recognize that their learning mechanisms properly reflect the actual ones. Natural language, however, is not such a simple phenomenon. Abstract models could include only simple learning mechanisms, which would be hard to deal with complicated phenomena appearing in natural language. The main challenge in language evolution is a lack of empirical data, that is, spoken language leaves practically no traces. Therefore, it would be helpful if there are language resources recorded in a long period with explicit description.

To solve this problem, we introduce a Japanese statutory corpus. In particular, we focus on legal terms defined in a provision, each of which consists of a tuple of a legal term and its explanatory sentences. Legal statutes are not only established but also often amended by changes in social situations. In some cases, legal terms are also revised, added, and deleted, depending on the scale of the amendment. Therefore, an amendment to provisions for legal terms implies a drastic change of the entire act. The terminology for legal terms must deal with such temporal changes that are dependent on amendment acts. Our purpose in this paper is to show the simulation models for language evolution properly deals with actual language changes.

We employ simulation models for grammar acquisition based on the iterated learning model (ILM) (Kirby, 2002), which shows a process of grammatical evolution through generations. This approach has often been used in simulation models concerning language evolution (Nakamura et al., 2015). One important reason for this comes from its robustness for syntactic learning from input sentences. As long as it is learning from a single parent, an infant agent receives sentences derived from a consistent grammar;

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it is possible to acquire a concise grammar.

This paper is organized as follows. In Section 2, we explain how to extract data for actual language changes from statutory texts. In Section 3, we introduce ILMs and our proposed model, which are examined in Section 4. Finally, we conclude in Section 5.

2 DIACHRONIC CHANGES IN LEGAL TERMS

In this section, we introduce diachronic changes in legal terms. Section 2.1 explains how to extract legal terms from statutory texts. Section 2.2 shows these evolutionary changes with examples.

2.1 Extraction of Legal Terms

Figure 1 shows an excerpt from the act dealing with the change of the term "Gas Business." The amended act is shown in Figure 2.[1]

What are recognized as legal terms to be collected depends on the purpose (Winkels and Hoekstra, 2012; Nakamura et al., 2016). In this paper, we define legal terms as those explicitly defined prior to use in a statute, each of which consists of a tuple of a legal term in the quotations and its explanation.

An article for definition of legal terms often consists of a number of paragraphs, each of which defines a legal term. They are described with boilerplate expressions including a legal term and its explanatory sentence, which can be extracted with a set of regular expression rules. The underlined phrases[2] in Figure 1 match one of the rules. As a result, the legal term "Gas Business" and its explanation can be extracted.

A defined term also appears in parentheses following a phrase as its explanation in the main text. Abbreviations of terms are often defined in parentheses. An example is shown in Figure 2, where the term "Specified Gas Generating Facility" is defined in parentheses. We extracted the explanation, the underlined part[2] in Figure 2, from the beginning of the definition to just before the beginning of the parentheses. Note that some explanatory sentences of a term include other legal terms as its hypernym or hyponym, which enables us to extract hyponymy relations between legal terms.

[1]We referred to the Japan Law Translation Database System (http://www.japaneselawtranslation.go.jp/) for the English translation of these acts. When there is no translation for the acts or act titles in the website, we manually translated them using the database.

[2]The original statute does not include the underlines, which were added by the author.

Gas Business Act (Act No. 51 of 1954)

(Definitions)
Article 2 (1) <u>The term</u> "Gas Business" <u>as used in this Act shall mean</u> the business of supplying gas via pipelines to meet general demand.

Figure 1: Excerpt from the Gas Business Act (Act No. 51 of 1954).

Gas Business Act (Act No. 51 of 1954)

[As of October 12, 1970]

(Definitions)
Article 2 (1) The term "General Gas Utility Business" as used in this Act shall mean the business of supplying gas via pipelines to meet general demand (excluding, however, businesses generating gas at a gas generating facility prescribed in paragraph (3) and supplying such gas via pipelines). (*snip*)
(3) The term "Community Gas Utility Business" as used in this Act shall mean <u>the business of generating gas at a simplified gas generating facility specified by a Cabinet Order</u> (hereinafter referred to as a "Specified Gas Generating Facility") and supplying such gas via pipelines to meet general demand at not less than 70 gas service points within one housing complex.
(*snip*)
(5) The term "Gas Business" as used in this Act shall mean a General Gas Utility Business or Community Gas Utility Business.

Figure 2: Excerpt from the Gas Business Act (Act No. 51 of 1954) as of October 12, 1970.

We successfully extracted legal terms, their explanations, and their relations. We found 27,737 terms and 36,698 relations. The precision of the relations was 88.0%, which might be improved with additional regular expression rules (Nakamura et al., 2016). The diachronic terminology shows legal terms evolves reflecting the social change, although legal documents are the most conservative in terms of language change.

2.2 Example of Diachronic Change

We cite the Gas Business Act (Act No. 51 of 1954) as an example to explain diachronic changes in legal terms. As of 2013, this act has been amended 34 times, at least five of which include the revision of terms and definitions in Articles 2 and 39-2. Figures 3(a) to 3(c) show the diachronic changes in the terms at three time points:

(1) At the new enactment, only two terms, "Gas Business" and "Gas Facilities," were defined in the Gas Business Act (Act No. 51 of 1954), which came into effect as of April 1, 1954 (Figure 3(a)).

(2) The term "Gas Business" was changed to "General Gas Utility Business," which became a hyponym of the newly defined term "Gas Business" with the newly added term "Community Gas Utility Business," by the Act on the Partial Amendment of the Gas Business Act (Act No. 18 of 1970), which came into effect as of October 12, 1970. Likewise, the term "Gas Supplier" and its hyponyms "General Gas Utility" and "Community Gas Utility" were defined. So was the term "Specified Gas Generating Facility" as an isolated term. Note that, unlike language changes as a natural phenomenon, the sense of legal terms was forced to change on the enforcement date (Figure 3(b)).

(3) As of the enforcement of the Act for the Partial Revision of the Electricity Business Act and the Gas Business Act (Act No. 92 of 2003), the number of terms defined in the Gas Business Act was increased to 15 (Figure 3(c)). In the period between (2) and (3), the terms "Class-I Gas Equipment," "Class-II Gas Equipment" and "Wholesale Supply" were defined, but deleted later. In addition, the term "Intra-Area Wheeling Service" was replaced with "Wheeling Service." These were basically eliminated by social selection.

3 ITERATED LEARNING MODELS

In this section, we introduce iterated learning models for learning grammar in the environment of legal terms. First, we briefly explain Kirby's ILM (KILM). Next, we introduce the modification for taking cognitive biases into account. Finally, we make some minor changes to adapt the model to the new environment.

3.1 KILM

Kirby (Kirby, 2002) introduced the notions of compositionality and recursion as fundamental features of grammar, and showed that they make it possible for a human to acquire compositional language. Figure 4 illustrates KILM. In each generation, an infant can acquire grammar in his/her mind given sample sentences from his/her mother. After growing up, the infant becomes the next parent to speak to a newborn baby with his/her grammar. As a result, infants can develop more compositional grammar through the generations. Note that the model focuses on the grammar change in multiple generations, not on that in one generation. Also, Kirby adopted the idea of two different domains of language (Bickerton, 1990; Chomsky, 1986), namely, I-language and E-language; I-language is the internal language corresponding to a speaker's intention or meaning, while E-language is the external language, that is, utterances. In his model, a parent is a speaker agent and his/her infant is a listener agent. The speaker agent gives the listener agent a pair of a string of symbols as an utterance, and a predicate-argument structure (PAS) as its meaning. A number of utterances would form compositional grammar rules in a listener's mind, through the learning process. This process is iterated generation by generation, and converges to a compact, limited number of grammar rules.

According to KILM, the parent agent gives the infant agent a pair of a string of symbols as an utterance, and PAS as its meaning. The agent's linguistic knowledge is a set of a pair of a meaning and a string of symbols, as follows.

$$S/love(john, mary) \rightarrow \text{hjsbs}, \tag{1}$$

where the meaning, i.e., the speaker's intention, is represented by a PAS *love(john, mary)* and the string of symbols is the utterance "hjsbs"; the symbol '*S*' stands for the category Sentence. The following rules can also generate the same utterance.

$$\begin{array}{rcl} S/love(x, mary) & \rightarrow & \text{h}\, N/x \;\text{sbs} \\ N/john & \rightarrow & \text{j}, \end{array} \tag{2}$$

where the variable x can be substituted for an arbitrary element of category N.

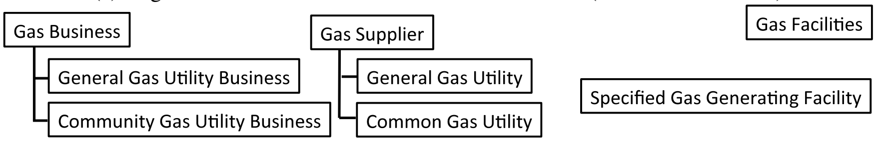
The infant agent has the ability to generalize his/her knowledge with learning. This generalizing process consists of the following three operations (Kirby, 2002): *chunk*, *merge*, and *replace*.

Chunk. This operation takes pairs of rules and looks for the most-specific generalization.

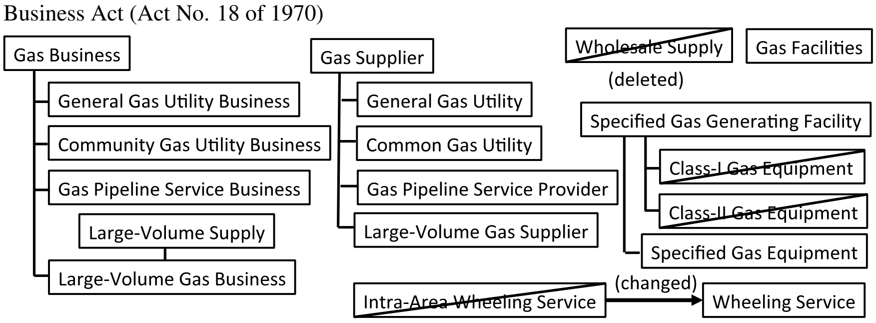
$$\begin{array}{l} \left\{ \begin{array}{rcl} S/love(john, pete) & \rightarrow & \text{ivnre} \\ S/love(mary, pete) & \rightarrow & \text{ivnho} \end{array} \right. \\ \Rightarrow \left\{ \begin{array}{rcl} S/love(x, pete) & \rightarrow & \text{ivn}\, N/x \\ N/john & \rightarrow & \text{re} \\ N/mary & \rightarrow & \text{ho.} \end{array} \right. \end{array} \tag{3}$$

Merge. If two rules have the same meanings and strings, replace their non-terminal symbols with one common symbol.

(a) Legal terms and relations in the Gas Business Act (Act No. 51 of 1954)



(b) Legal terms and relations as of enforcement of the Act on the Partial Amendment of the Gas Business Act (Act No. 18 of 1970)



(c) Legal terms and relations as of enforcement of the Act for the Partial Revision of the Electricity Business Act and the Gas Business Act (Act No. 92 of 2003)

Figure 3: Dynamics of definitions in the Gas Business Act.

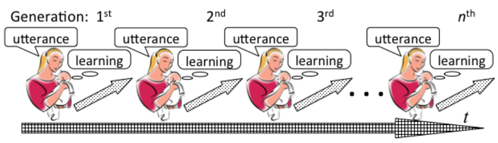


Figure 4: Iterated learning model.

Replace. If a rule can be embedded in another rule, replace the terminal substrings with a compositional rule.

In Kirby's experiment (Kirby, 2002), a constant number of predicates and object words (five for example) are employed. Also, two identical arguments in a predicate like *love(john, john)* are prohibited. Thus, there are 100 distinct meanings (5 predicates $\times$ 5 possible first arguments $\times$ 4 possible second arguments) in a meaning space.

The key issue in ILM is to create a *poverty of stimulus*, which explains the necessity of universal grammar (Chomsky, 1980). Kirby (Kirby, 2002) modeled it as learning through bottlenecks, which are rather necessary for the learning. As long as an infant agent is given all sentences in the meaning space during learning, he/she does not need to make a compositional grammar; he/she would just memorize all the meaning-sentence pairs. Therefore, agents are given a part of sentences in the whole meaning space. The total number of utterances the infant agent receives during learning is parameterized. Since the number of utterances is limited, the infant agent cannot learn the whole meaning space; thus, to obtain the whole meaning space, the infant agent has to generalize his/her own knowledge by self-learning, i.e., *chunk, merge,* and *replace*. The parent agent receives a meaning selected from the meaning space, and utters it using his/her own grammar rules. When the parent agent cannot make an utterance because of a lack of grammar rules, he/she invents a new rule. This process is called *invention*. Even if the invention does not work to complement the parent agent's grammar rules, he/she utters a randomly composed sentence.

3.2 Meaning Selection ILM with Cognitive Biases (MSILMB)

The iterated learning model has been expanded for examining the relationship between language acquisition and cognitive biases. Several studies have suggested that cognitive biases work effectively in the first language acquisition (Imai and Gentner, 1997; Markman, 1990). Cognitive bias, which is common to all human beings, involves systematic errors in judgment and decision-making due to cognitive limitations, motivational factors, and/or adaptations to natural environments (Wilke and Mata, 2012).

These biases work in a joint attention framework where two individuals, a parent and an infant, share a state of an environment. For example, the parent and infant are looking at a rabbit which are eating carrots, and the parent utters 'Gavagai.' In this situation,

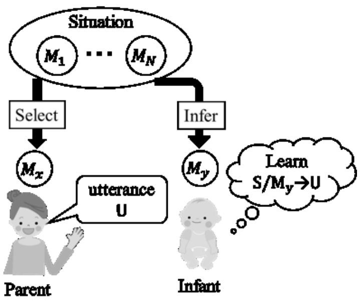


Figure 5: Learning Process on Meaning Selection ILM.

the infant cannot infer the meaning of 'Gavagai' logically, i.e., there are many possibilities of its meaning, such as a rabbit, a white animal or an action of eating. This problem is well known as Gavagai problem (Quine, 1960). The learning environment of infants in first language acquisition is very close to this situation. However, they overcome this problem, and acquire their first language at an overwhelming pace. For this infants' phenomenal learning, several studies have suggested that the infants infer meanings efficiently to limit possibilities in a situation using constraints, that is cognitive biases, and identify a meaning of the utterance (Imai and Gentner, 1997; Hansen and Markman, 2009).

The Meaning Selection ILM (MSILM) (Sudo et al., 2016) employs the notion of a joint attention frame in KILM. Figure 5 shows an image of the learning process on MSILM, in which both parent and infant agents share a situation. The parent agent selects a part of the situation (M_x) which contains multiple meanings $\{M_1,\dots,M_N\}$, and utters U about it to the infant agent. Once receiving the utterance, he/she infers its meaning from the presented situation, and learns a pair of the utterance U and its meaning M_y. Thus, the infant agent does not always infer the same pair as the parent's knowledge, that is, the infant agent would acquire the grammar rule $S/M_y \to U$, while the parent's utterance was derived from his/her knowledge of $S/M_x \to U$.

Some cognitive biases have been employed to MSILM, and their effectiveness was verified on simulation of the first language acquisition (Sudo et al., 2013). Hereafter, we call MSILM with cognitive biases MSILMB, which employed the following biases:

Symmetry Bias: When the predicate $p \to q$ is true, the symmetry bias allows humans to mislead $q \to p$ being also true. A pair of p and q is put as a pair of label and object (Imai and Gentner, 1997), a pair of meaning and utterance (Matoba et al., 2010) and so on. If an infant agent can generate the same utterance as the parent agent's, and its meaning is found in the presented meaning, he/she connects the utterance and the meaning. Otherwise, the infant agent selects one out of the presented meanings randomly.

Mutual Exclusivity Bias: This is the assumption that only one label can be applied to each object in early word learning (Markman, 1990). If an infant agent has already acquired the grammar rule $S/M \to U_1$, he/she dose not connect the meaning M to any other utterances. In other words, if the infant agent can generate the utterance of a presented meaning M' in a situation with his/her acquired grammar and the generated utterance is not the same as the parent agent's, the infant agent deselects M' from the candidate of the meaning of the parent agent's utterance.

These biases work as "one utterance to one meaning (symmetry bias)," and "one meaning to one utterance (mutual exclusivity bias)," i.e., the effect of these biases gives a one-to-one relation between a meaning and an utterance to the infant agent under a multiple cognition environment like a joint attention frame.

3.3 Our Model

We basically employ MSILMB in infant agents' learning process. We assume that a parent-infant pair shares their situation in the environment.

Our model differs from the former one (Sudo et al., 2013) as follows:

- The situation can be changed about a set of legal terms and their relations by amendment from generation to generation. Some terms and relations remain the same, while the others are deleted, newly added, or replaced with others.
- The actual meaning space is a subset of the whole meaning space; speakers can only speak a scene of the actual situation, while they randomly choose a meaning from the whole meaning space in the former model.
- The number of utterances varies depending on the situation. It is calculated as (the size of the whole meaning space in generation)$/2$.

4 EXPERIMENTS

4.1 Experimental Settings

Our experiments aim to examine whether KLIM and MSILMB properly work in actual situations over the diachronic change. In order to reproduce the actual diachronic change, we pick up legal terms defined in the Gas Business Act (Act No. 51 of 1954) from the Japanese statutory corpus. In the situation, agents have knowledge about objects corresponding to legal terms and their relations. One generation in the simulation corresponds to a year in the actual world.

We defined three predicates; one represents a state of isolation *is_isolated*, and the others are for hyponymy relations, that is, *is_hypernym_of* and *is_hyponym_of*. The number of objects n varies along with amendments. Therefore, the size of the whole meaning space is calculated as (2 predicates for hyponymy relations $\times$ n possible first arguments $\times$ $(n-1)$ possible second arguments + 1 predicate for a state of isolation $\times$ n possible arguments). Table 1 shows the size of the whole meaning space, the size of actual meaning space and the number of utterances in each generation, which corresponds to years after enforcement of the act.

In KILM, agent's linguistic knowledge is evaluated by expressivity and the number of grammar rules. Expressivity is defined as how much of the whole meaning space the agent can utter with his/her grammar rules. In MSILMB, it is important how much the infant agent acquired language close to the parent agent's. Therefore, to evaluate the similarity between two languages, we employed the language influence rate, which is based on similarity between two character strings. The language influence rate is calculated at the end of each generation by comparing between the enumerations of sentences whom both parent and infant agents can utter with their grammar rules (See (Nakamura et al., 2015) for more details of the language influence rate, which is called language distance).

An utterance is expressed with a string of 10 types of letters. Agents can invent an utterance by invention in a range of 2 to 4 letters. A trial of the simulation stops at the 60th generation, which is the span between the enforcement of the Gas Business Act and that of the last amendment act with a 10-year-blank for learning.

We compare experimental results of KILM and MSILMB; in the former, since infants receive a pair of a meaning and a string of symbols from parents, agents are expected to acquire compositional grammar. Meanwhile in the latter, infants receives only a string of symbols, which implies they need to infer what parents talk about. The learning is more difficult, but its learning environment is close to the actual one.

4.2 Experimental Results

We show experimental results in Figure 6, in which all the lines are plotted by average of 100 trials.

Figure 6(a) shows the rate of actual meanings infants can utter by generation. This shows how much agents can represent actual situations using their grammar rules. Note that the actual meaning space is a subset of the whole meaning space. For example, in the generations from 1 to 16 corresponding to Figure 3(a), there are only two actual situations, denoted by the meanings: *is_isolated(GasBusiness)* and *is_isolated(GasFacilities)*. If the parent agent utters both of them in the limited number of utterances, that is 3, his/her infant can learn both utterances. In addition, if those utterances share a common substring in different meanings, the infant can extract a compositional rule denoting *is_isolated(X)* by *chunking*.

Overall, since this process is common in KILM and MSILMB, the result shows almost the same. Since the number of utterances is much more than that of the actual meanings, infant agents are likely to listen to all kinds of utterances for the actual meanings in a generation.

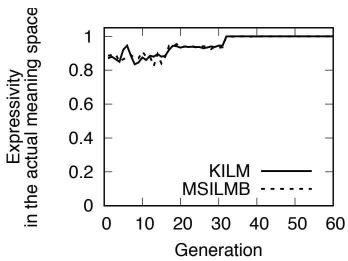
Figure 6(b) shows expressivity in the whole meaning space by generation. The thin solid line denotes the border of compositionality, which is calculated as (*Size of actual meaning space*)/(*Size of the whole meaning space*). If the expressivity exceeds it, the grammar is regarded as compositional. In the early generations, expressivity in the both models shows around 0.3, because there are 2 actual meanings against 6 possible patterns. After the first amendment at the 17th generation, the expressivity suddenly dropped down. This is because the number of possible meaning patterns rose from 6 to 120 due to the growing number of legal terms from 2 to 8.

Figure 6(c) shows the normalization by the number of actual meanings for Figure 6(b). Therefore, the value less than 1 implies agents do not learn compositional grammar, which suggests that agents can utter little other than what they heard until the 31st generation. This is because agents receive 60 utterances for 10 actual meaning patterns. In other words, they are not exposed to *poverty of stimulus*, which is supposed to promote learning compositional grammar. As a result, they just seem to memorize all the utterances from their parents during the 17th to 31st generation.

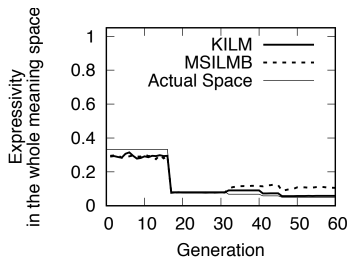
We can see if agents learn compositional grammar by checking the number of grammar rules they acquired. Figures 6(d) and 6(e) show the number of rules by generation in KILM and MSILMB, respectively. Note that decreasing sentence rules and increasing word rules imply that acquired grammar is

Table 1: Number of utterances based on meaning space in each generation.

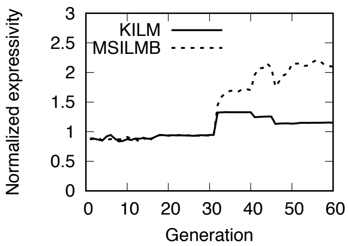
Year From / To	1954 1969	1970 1984	1985 1993	1994 1998	1999 2002	2003 2014
Generation	1-16	17-31	32-40	41-45	46-49	50-60
Number of objects	2	8	10	13	14	15
Number of isolated objects	2	2	1	1	3	2
Number of hyponymy relations	0	8	12	18	16	20
Size of the whole meaning space	6	120	190	325	378	435
Size of the actual meaning space	2	10	13	19	19	22
Number of utterances	3	60	95	163	189	218



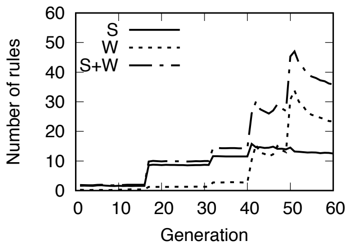
(a) Expressivity in the actual meaning space



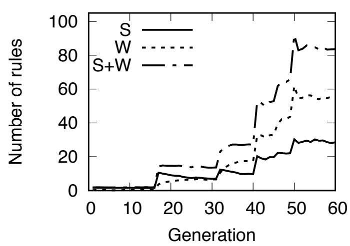
(b) Expressivity in the whole meaning space



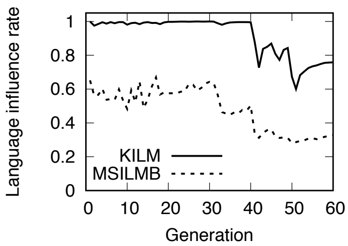
(c) Normalized expressivity



(d) Number of grammar rules in KILM (S: sentence, W: word)



(e) Number of grammar rules in MSILMB (S: sentence, W: word)



(f) Language influence rate

Figure 6: Experimental Results.

compositional. During the 17th to 31st generation, agents in KILM keep around 10 sentence rules for 10 actual meanings, while those in MSILMB seem to have a decreasing number of sentence rules. The same can be seen during the 32nd to 40th generation. Since the symmetry bias works well, agents make similar utterances regard to have similar meanings. Furthermore, the mutual exclusivity bias prevent agents from making inconsistent rules, which facilitates acquisition of compositional grammar. As a result, the normalized expressivity of MSILMB exceeds that of KILM from the 32nd generation due to high compositionality.

Learning compositional grammar enables agents to represent even inexperienced situations. From this viewpoint, as far as seeing Figure 6(b), neither KILM nor MSILMB is enough for representing the whole meaning space. This is because the learning period in 60 generations is too short.

The problem of MSILMB is that grammatical learning is far from matching actual meanings. In fact, it is not always true that similar utterances have similar meanings. Figure 6(f) shows the language influence rate by generation. KILM keeps higher than MSILMB in the influence rate, which denotes agents in KILM are more likely to speak similar language to their parents. This is characteristics of MSILMB, in which learning compositionality takes priority over interpretation of utterances. For example in the situation of Figure 3(a), when a parent agent utters “`bus`” and “`fac`” for *is_isolated(GasBusiness)* and *is_isolated(GasFacilities)*, his/her infant agent may misunderstand the former utterance corresponds to the latter meaning, and vice versa. This phenomenon could cause the decrease of the language influence rate.

Through the experiments, we showed agents in MSILMB properly acquired compositional grammar in the actual situation of language change. An excerpt of grammar rules that the infant agent acquired at the 60th generation in a trial is shown in Equation (4).

$$\begin{cases} S/x_0(x_1,x_2) & \rightarrow & C_{10}/x_0\, C_{16}/x_1\, C_{17}/x_2 \\ C_{10}/is\_hypernym\_of & \rightarrow & \text{ei} \\ C_{10}/is\_hyponym\_of & \rightarrow & \text{a} \\ C_{16}/CommunityGasUtilityBusiness \rightarrow \text{e} \\ C_{16}/LargeVolumeGasBusiness \rightarrow \text{e} \\ C_{17}/GasBusiness & \rightarrow & \text{febja} \\ S/isolate(x_1) & \rightarrow & \text{e}\, C_{11}/x_1 \\ C_{11}/GasFacilities & \rightarrow & \text{hbfj} \\ C_{11}/WheelingService & \rightarrow & \text{hieb}, \end{cases} \quad (4)$$

where S, C_{10}, C_{11}, C_{16} and C_{17} are non-terminal symbols as a category name, and x_0, x_1 and x_2 are variables.

5 CONCLUSION

In this paper, we introduced a diachronic legal terminology to simulation models to confirm proposed models properly deal with natural language phenomena. Legal terms are defined in statutes, in which they are added, deleted, or replaced with others reflecting social change. Therefore, the change of legal terms and their relations is unstable and not coherent.

We used KILM and MSILMB for learning compositional grammar under the environment. As a result, KILM showed agents acquired less compositional grammar due to a difficult learning environment. Meanwhile in MSILMB, agents succeeded to deal with the environment, although their grammar is less influenced on their parents' one.

Our achievement could contribute to not only language evolution, but also some novel field of language processing, because it is a part of huge and complex problem of creation of systems with learning (self-learning) abilities to the reactions in previously unknown situations. For example, it would be useful for creation of constantly expending library of actions for robots working on another planets.

Integration of language evolution and legal knowledge is a challenging theme. Our analysis of the statutory corpus revealed that statutes are excellent data for pursuing actual language change. Although we, in this paper, chose the Gas Business Act by chance, further analysis would lead to synthetic characteristics of legal terms.

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