Chinese Learning of Semantical Selectional Preferences Based on LSC Model and Expectation Maximization Algorithm

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***Abstract*—Aiming at the situation of current Chinese language resources shortage ,this paper proposes semantically selectional preferences of unsupervised learning method, and presents a strategy of obtaining verb-noun semantic collocation in Chinese. An approach of Chinese semantic preference learning, which is based on Latent Semantic Clustering model and Expectation Maximization Algorithm. First, the parameters are initialized randomly. Second, a certain number of training iterations is performed until convergence. Each iteration consists of expectation step and maximization step. Finally, the semantic association between verbs and nouns are calculated as a measure of its matching probability. This method can be used on Chinese without syntax-annotated corpora. Lots of experiment results show that LSC provides proper patterns of verb-noun collocation semantically. The algorithm converges quickly.**

***Index Terms*—selectional preferences, Latent Semantic Clustering(LSC), clustering selectional preferences, Expectation Maximization(EM) , unsupervised learning**

I. INTRODUCTION

Semantically selectional preferences are emphasized by the researchers both in areas of linguistics and natural language processing (NLP). People regard it as an effective tool to improve the efficiency of language analysis. Semantically selectional preferences can be applied to, such as semantic analysis of syntactic structures[1], eliminating ambiguity of meaning[2,3], vocabulary classification[4,5], capturing of lexically semantic relations[6], metaphor[7] and labeling semantic role[8,9] etc.. At present the acquisition method can be roughly divided into three types: ① knowledge-based method, such as using the relation between upper and lower noumenon; ②statistics-based method, such as the introduction of the vector space model [10], cluster model [11], topic model[12], similar model[13], etc.; ③ the combination of knowledge and statistics-based method [3] (Comparative research of three methods can be found in the literature [14]). Most studies on semantically selectional preference focused on English[1-14], relatively little attention on Chinese[15-17].

This paper presents a strategy of obtaining verb-noun semantic collocation on Chinese. The advantages are: 1) using unsupervised learning methods, language materials labeled by grammar are not needed, the support from noumenon is neither needed. It's in line with the situation of Chinese language resources shortage; 2) based on the soft clustering method, it can effectively overcome the disadvantage resulting from the sparse data in corpus study; 3) it calculates the possibility of collocation of verbs and nouns in accordance with their semantic association degree, reduces the influence of the amount of man-made provision model on learning effects;4) the algorithm converges faster, costs time less.

The paper is organized as the following, section II describes the semantically selectional preferences; section III introduces the latent semantic clustering (Latent Semantic Cluster) model; section IV dwells on the process of learning semantically selectional preferences; section V shows the results of experiments and discusses them; finally concludes the whole paper.

II. SELECTIONAL PREFERENCES

Semantically selectional preferences usually refers to the predicate verb's semantic selectional restriction against its argument. A particular verb is inclined to choosing a particular noun as its object and this is a two-way choice. It's the same from the perspective of nouns. Such as "have - meals", "wear - clothes" and so on, which has been already studied in Chinese linguistics, but the study is relatively late from the perspective of computer processing.

Broadly speaking, semantically selectional preferences can refer to the tendency of all words. This paper not only studies the predicate verb in argument selection, but concerning an semantic collocation rules of verb and noun, similar to English verb-noun phrases.

III. LSC MODEL

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A. Model Introduction

Latent Semantic Clustering (LSC) model was first proposed by Rooth for disambiguation of grammatical structure [18], A. Wagner's doctoral thesis[19] is based on the model to achieve disambiguation of word sense, clustering of syntactic structure and so on. Assuming that the verb set V = {v_1, v_2, ... v_m}, noun set N = {n_1, n_2, ... n_k}, defining the selection mode as <V',N'> , in it $V' \subseteq V, N' \subseteq N$, choice model is the collection of these choices, and this is a concept model. LSC converts it into probabilistic model that is replacing the eigenfunction set with distributing pattern of probability. Accordingly, we define the choice model C = {c_1, c_2, ... c_l} as a pair of dispersing distributions of values respectively based on verbs and nouns, expressed as the following:

$$< \lambda v P(v \mid c), \lambda n P(n \mid c) > \quad \sum_{v \in V} P(v \mid c) = 1 \quad \sum_{n \in N} P(n \mid c) = 1 \quad c \in C \ (1)$$

In it, the function $\lambda v P(v \mid c)$ maps the verb v as a value at the interval (0,1), and meets the restrictions that the sum of all verbs value equals 1 in the same pattern, nouns are similar.

Assuming that P (c), P (v | c) and P (n | c) are independent of each other, the distributing pattern of probability on structure $V \times N$ based on a particular model c is as the following:

$$P(v, n \mid c) = P(v \mid c) \times P(n \mid c) \quad v \in V, n \in N, c \in C \ (2)$$

We can also construct a distributing pattern of probability on $C \times V \times N$ as:

$$P(c, v, n) = P(c) \times P(v \mid c) \times P(n \mid c) \ \ v \in V, n \in N, c \in C \ (3)$$

The sum of all modes in equation (3),that

$$P(v,n) = \sum_{c \in C} P(c,v,n)$$
$$= \sum_{c \in C} P(c) \times P(v \mid c) \times P(n \mid c) \, v \in V, n \in N, c \in C \ (4)$$

A possible example of clustering LSC model in TABLE I:

LSC model is a soft clustering method, which means a pair of verb and noun not absolutely belonging to a model or not, but to some extent belonging to a certain model. This degree is the probability P (v, n | c), for example, the probability of the figure above "increase – force"

TABLE I
EXAMPLE OF LSC MODEL CLUSTERING

verb(v)	P(c)=0.003524		
	P(v|c)	noun(n)	P(n|c)
发展	0.168923	效率	0.048504
增强	0.397566	水平	0.092840
提高	0.549743	能力	0.108522
加大	0.742414	力度	0.198542

belonging to mode c is 0.14740333(0.742414 × 0. 198546). But in the actual model fitting, we do not directly use the joint probability P(v,n|c) of v and n as a parameter, but use marginal probability P (v | c), P (n | c) as parameters, and then estimate parameter values by using expectation maximization algorithm (EM).

B. Estimation of Parameters by EM

The view data (incomplete) of LSC model is the common frequency freq (v, n) of verb v and noun n, the value can be obtained from the corpus; the corresponding invisible data (complete) is triples (c, v, n), parameters are P (c), P (v | c), P (n | c) respectively.

Then the EM algorithm alternates as the following two steps until convergence:

(1) E-step, calculate the mathematical expectation E (c, v, n) of triples (c, v, n) by using the current parameter value estimated;

For a given model, the probability of visual data (v, n) generated from the pattern c can be expressed as $\frac{P(c, v, n)}{P(v, n)}$, so the occurring mathematical expectation of the event <c,v,n> is:

$$E(c, v, n) = freq(v, n) \times \frac{P(c, v, n)}{P(v, n)} \qquad (5)$$

P (c, v, n) and P (v, n) are calculated according to the formula (3) and formula (4).

(2) M-step, in accordance with the formula (6), (7), (8), update the parameter value based on the mathematical expectation E (c, v, n).

$$P(v \mid c) = \frac{E(c, v)}{E(c)} \qquad (6)$$

$$P(n \mid c) = \frac{E(c, n)}{E(c)} \qquad (7)$$

$$P(c) = \frac{E(c)}{\sum_{v \in V, n \in N} freq(v, n)} \qquad (8)$$

The calculation of E (v, c), E (n, c) and E (c) can be understood fully at one glance:

$$E(c, v) = \sum_{n \in N} E(c, v, n)$$
$$E(n, c) = \sum_{v \in V} E(c, v, n)$$
$$E(c) = \sum_{v \in V, n \in N} freq(v, n) \qquad (9)$$

IV. ACQUISITION OF SEMANTICALLY SELECTIONAL PREFERENCES BY USING OF LSC

The process of acquisition of semantically selectional preferences in this paper is as the following:

(i) Giving initial values to the three model parameters P (v | c), P (n | c), P (c), meeting the conditions

$$\sum_{v \in V} P(v \mid c) = 1 \ \sum_{n \in N} P(n \mid c) = 1 \ \sum_{c \in C} P(c) = 1$$

(standardization of mode is not required);

(ii) Calculation of mathematical expectation E (c, v, n) according to the formula (5);

(iii) Re-calculating parameter values P (v | c), P (n | c), P (c) respectively by using formula (9) and formula (6), (7), (8) ;

(iv) Calculating semantic collocation probability of the verb v and the noun n based on formula (4);

(v) Choosing m <v,n> combinations from the front by descending order of P (v, n);

(vi) Implementing step (2) - (5) circularly, until convergence, stop the algorithm.

V. EXPERIMENT

Because there is no "gold standard" for semantically selectional in Chinese, we manually construct a table of semantic collocation according to the vocabulary selected. Experiments show that, on the basis of the LSC's approach, we can learn semantic collocation of verbs and nouns knowledge effectively,meanwhile, the convergence is fast. The method is feasible.

A. Experimental Preparation

This paper uses the handmade labeling (word segmentation and POS tagging) corpus of the People's Daily (1998) as modeling objects, involving about 18,049 words. As the articles from People's Daily are relatively simple materials, such collocations as "have - meals, wear – clothes" are rarely seen, so such verbs and nouns are not selected. In the experiment, we take three sets of words; the specific numbers of each set of verbs, nouns are as Table Ⅱ.

B. Module

We give three modules to test experimental results, order correct to represent the identification numbers of right semantic collocation combination (the collocation in the "gold standard" which is identified with the method in the paper); algorithm represent the total number of combinations which is identified with the method in the paper; gold represent the manual number of semantic collocation in "gold standard". Then the precision, recall and F_1 are defined as follows:

TABLE Ⅱ
THE NUMBER OF VERBS, NOUNS IN THREE SETS IN THE EXPERIMENT

set	verbs	nouns
set1	16	14
set2	34	60
set3	49	97

$$\text{Precision} = \frac{\text{correct}}{\text{algorithm}} \times 100\% \qquad (10)$$

$$\text{Recall} = \frac{\text{correct}}{\text{gold}} \times 100\% \qquad (11)$$

$$\text{F1} = \frac{2 \times \text{correct}}{\text{algorithm} + \text{gold}} \times 100\% \qquad (12)$$

C. Relationship between Results and Initial Value

According to the method in this paper, the initial value is given at random, so the first problem in the experiment we have to discuss is whether the initial value will affect the results or not. Take 25 mode quantities from set 2, operate EM algorithm respectively 5 times from different initial values; 1,000 iterations, choose semantic collocation of verbs and nouns (in accordance with P(v,n) counting down 25 from the front). The results are shown in Fig.1. It is seen although the values of P (v, n) are a little different, the results of collocations remain basically unchanged. This shows that optimal results are independent of the initial values.

Initial value 1		Initial value 2		Initial value 3	
形成格局	0.102023	形成格局	0.001107	形成格局	0.001582
保护财产	0.092290	保护财产	0.000564	保护财产	0.000584
出现机会	0.049438	出现机会	0.000667	出现机会	0.000861
形成经验	0.036294	形成经验	0.000386	形成经验	0.000561
保护机制	0.035021	保护机制	0.000315	保护机制	0.000383
出现经验	0.033613	出现经验	0.000352	出现经验	0.000368
保护土地	0.032074	保护土地	0.000172	保护土地	0.000236
帮助经验	0.028213	帮助经验	0.000285	帮助经验	0.000224
面对土地	0.027203	面对土地	0.000907	面对土地	0.000104
把握机制	0.015450	把握机制	0.000255	把握机制	0.000219
培养机制	0.002505	培养机制	0.000065	培养机制	0.000000
存在时机	0.001555	存在时机	0.000008	存在时机	0.000010
出现机遇	0.003244	出现机遇	0.000124	出现机遇	0.000091
保持土地	0.002733	保持运动	0.000022	保持土地	0.000061
出现时机	0.004095	出现时机	0.000667	出现时机	0.000031
面对机会	0.003813	面对机会	0.000061	面对机会	0.000120
面对局势	0.003083	面对局势	0.000063	面对局势	0.000027
保持局势	0.001760	保持局势	0.000123	保持局势	0.000000
存在机遇	0.000178	存在机遇	0.000001	存在机遇	0.000002

Figure 0. Algorithm operation is independent of the initial value (shown in the data for the P (v, n) value).

D. Determination of Convergence

The purpose of semantically selectional preferences is to find semantic collocations combinations. If the algorithm's combinational contents of the i and the i-1 iterations are the same basically, it can be regarded as convergence more iteration is meaningless. Therefore, whether the semantic combinations of verbs and nouns will change is taken as a convergent basis in this paper.

Using changeprob as change rate, the formula is:

$$\text{changeprob} = \frac{\text{changenum}}{\text{totalnum}} \times 100\% \quad (13)$$

Changenum represents the changeable quantities of combinations between this iteration and next, including the changes of combination contents and sequences. Totalnum represents the total number of combinations, 100 is taken in this paper (according to P (v, n) counting down 100 from the front).

As changeprob value reflects the changes in results of adjacent iterations. It can be used as the criterion of convergence. To verify whether the algorithm is convergent, we take 3 sets as experimental objects, with the model number being 25 and calculating rate of change being changeprob. The results are shown in Fig.2.

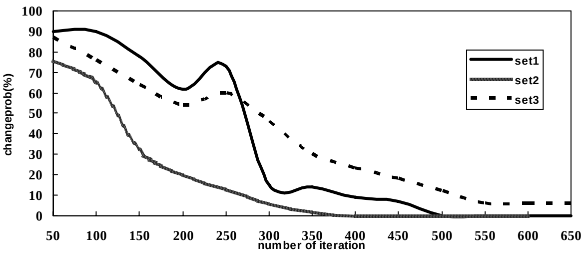

Figure 2. About 600-time Iterations, Algorithm Convergence.

It can be seen from the figure, although the number of verbs, nouns in three sets is different, the combination is basically fixed after 600-time iterations. At the same time it is also found in the experiment when set 3 occurs 600-time iterations, there is no completely invariable, the change rate is 6%; till 1000-time iterations, the change rate will be reduced to about 1%, then there will be ups and downs, but no more than 6%. Without taking the order of combination into consideration, the combination does not basically change after iterations about 300 times, which shows the algorithm convergence.

It takes about dozens of seconds (less than 1 minute) for set 3 to iterate 600 times. It takes less time for set 1 and set 2. Therefore, the EM method based on LSC's is completely feasible from the time-cost point of view.

E. Determination the Number of Model

The direct use of LSC model is to achieve the possibility of accumulation to the same model for a verb-noun pair by calculating P (v | c), P (n | c) to understand grammatical, semantic features of verbs and nouns in the same model. The drawback of this method is that the number of modes has a great influence on clustering results, as shown in Fig.3.

c1	c2	c3	c4	c5
出现 机会	形成 目标	把握 经验	安排 生活	保护 经济
形成 经验	形成 机遇	把握 目标	安排 工作	保卫 祖国
保护 机制	形成 时间	把握 速度	存在 公司	保护 计划
存在 机会	安排 比赛	把握 经济	安排 计划	保卫 和平
面对 机遇	形成 人才	把握 效益	安排 时间	保护 财产

(a) the number of clustering modes is five

c1	c2	c3	c4	c5
培养 学生	提高 效益	参加 工作	参观 医院	安排 生活
培养 能力	提高 认识	参加 会议	参观 工厂	安排 工作
改善 生活	提高 国家	统一 思想	参观 机构	安排 任务
培养 技术	加大 力度	参加 运动	参观 服务	安排 计划
改善 经济	提高 效率	参加 比赛	参观 信息	安排 时间

c6	c7	c8	c9	c10
形成 机制	安排 技术	出现 计划	提供 服务	处理 能力
形成 经济	安排 工作	出现 人才	提供 经验	处理 软件
形成 思想	安排 任务	出现 时机	提供 技术	处理 效率
形成 价格	安排 时间	面对 生活	提供 工作	处理 比赛
形成 工作	把握 经济	面对 机会	提供 机会	处理 经济

(b) the number of clustering modes is ten

Figure 3. The number of modes is different, clustering results are extremely different.

For the fixed conceptual groups of verbs and nouns, excessive number of models will lead to appearance of unrelated semantic collocations, but if the number is too small, some combinations of verbs and nouns will lose. General literatures [18,19] are subjective to fix the number of models, it's hard to verify the experimental results theoretically. In this paper, verb's choice towards noun is directly obtained by calculating P (v, n), the number of modes need not to be considered too much.

We carry out experiments with set 2, taking the total number of combinations for 10, 30, 50 (according to P (v, n) counting down 10, 30, 50 from the front), still calculate the change rate (considering that the ordering of verbs and nouns has little effect on the results of semantically selectional preferences, so only changes in the content is considered) by formula (10). The results are shown in Fig. 4.

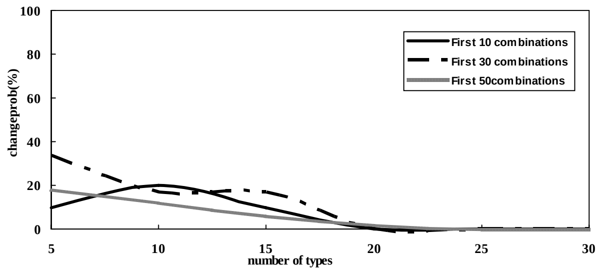

Figure 4. The number of models is more than 20, results of semantic collocation are basically unchanged.

F. Results and Discussion

For three sets, the numbers of modes are all taken 25 with iterations 1000. Considering all semantic combinations of P (v, n)> 0.0005, calculate precision, recall and F_1 respectively. The results are shown in TABLE Ⅲ.

TABLE Ⅲ
THE PRECISION, RECALL AND F_1 VALUES OF THREE SETS

	precision(%)	recall(%)	F_1(%)
set1	72.00	81.33	75.68
set2	83.42	85.13	84.24
set3	69.80	70.66	70.34

It can be seen from the TABLEⅡ, the experimental results of set 2 are the best, because verbs, nouns in experiment 2 occur more frequently in the modeling corpus, with an abundance of information; the choice of words in set 1 is so few, a lot of irrelevant collocations occur after EM iteration, leading to the results are not so ideal as set 2; some corpus of words occurs too little in set 3, the accuracy decreases.

Recall is a little higher than precision, indicating that this method generates some "superfluous" collocations. By analyzing them, a lot are due to the lack of grammatical information, such as "form – land, reform –

efforts, develop – sports", etc. Although the noun occurs after the verb for several times in the sentence, there is an attributive before it or a headword after it. It is not the word matches the verb. If the study is aiming at the corpus labeled by grammar, the accuracy will be greatly improved.

In the experiment, we take semantic combinations according to P (v, n)> 0.0005. We get about 59 vocabulary pairs in set 1, 168 in set 2, 326 in set 3. If the number of combinations is fixed, for example, choosing the first 10, 30, 50 according to P (v, n) counting down, the accuracy can be higher, but the recall rate will be down. Fig.5 is about results of set 2 as the experimental subjects.

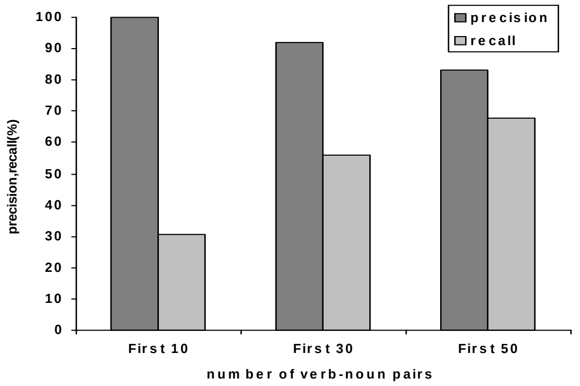

Figure 5. Comparison between accuracy and recall, choosing the first 10, 30, 50 combinations by P (v, n) in counting down sequence.

Fig.5 shows that P (v, n) values can reflect the semantic collocation relevance of verbs and nouns. The higher the P (v, n) value is, the more likely the verb matches the noun.

There are a lot of studies about semantically selectional preferences in English[1-14]. But the testing is generally conducted for the classification mode. It is inappropriate to compare the result with that in this paper.

VI. Conclusion

The knowledge of semantically selectional preferences is very important for NLP, but at present Chinese research in this area is relatively small. This paper attempts to take advantage of EM method which is based on LSC model to get semantic collocation information of verbs and nouns from raw corpus. The experimental results show that the method is feasible. Future work will focus on further studying semantically selectional preferences in Chinese from following three aspects: ① Combine the ontology library by using appropriate strategy; ② Consider taking corresponding vocabulary by means of corpus instead of fixed collection of verbs and nouns; ③ Increase the forms and content of corpus more rich for the model training.

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