# Beyond Selectional Preference: Metaphor Recognition with Semantic Relation Patterns

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**Abstract**

*This paper analyzes the limitations of selectional-preference based metaphor recognition, and proposes a new model for metaphor recognition, using Chinese subject-predicate construction as illustration. After showing with experiments that selectional-preference based metaphor recognition has difficulty in recognizing conventional metaphors and literal expressions with low frequency, the paper presents a metaphor recognition model which is based on Semantic Relation Pattern, a distribution pattern integrating six types of semantic relations between a subject head and other subject heads within a subject-predicate cluster, and employs a SVM classifier for metaphor recognition. Contrastive Experiments show that the proposed model achieves an F1 of 89% in metaphor recognition, about 37% higher than the selectional-preference based model. Further analysis shows that the proposed model is able to account for lexicalized metaphors, truth-condition literality and other types of literality and metaphor failed in selectional-preference based models. More importantly, the proposed model possesses the ability to generalize to unknown predicate heads. Theoretically, the semantic-relation-pattern model can also be applied for metaphor recognition in other endocentric constructions such as verb-objects and adjective-nouns.*

**Keywords**

*Metaphor recognition; selectional preference; semantic relation pattern; SVM.*

## 1 Introduction

Metaphor contrasts with literal expression and metonymy as a type of semantic interpretation, as are exemplified in Example 1, where 1(a) and 1(d) are literal, 1(b) is metonymic and (c) is metaphorical. The inquiry about how metaphor functions comes from various disciplines

**Example 1.**

(a) 病人(the patient) 悲伤(is sad)
(b) 全国(the country) 悲伤(is sad)
(c) 天空(the sky) 悲伤(is sad)
(d) 老人(the old) 悲伤(is sad)

such as philosophy, linguistics, artificial intelligence and others, as it is not only a way to express meaning, but also a driving force of semantic change (Carbonell, 1980; Wilks & Catizone, 2002) and a cognitive device(Lakoff & Johnson, 1980). Understanding metaphor is also a necessary step to improve performance of Q&A system, information retrieval, machine translation and other NLP systems (Barnden, 2008; Yu et al, 2006).

Metaphor understanding generally consists of two phases: recognition and interpretation (Zhou, 2009). Metaphor recognition premises interpretation of metaphor. It can be regarded as a task of classification in which a given linguistic construction is grouped into literal expression, metonymy, metaphor or some other types of interpretation, on the basis of context which generally varies from word level to discourse. As such, the task of metaphor recognition generally involves three issues: criteria of classification, knowledge source, and algorithm for classification. The criteria of classification is mainly concerned with the question of what constitutes a metaphor, a metonym, or a literal expression. The knowledge source is about what types of knowledge are employed to perform the classification. The algorithm for classification specifies the algorithm used for tagging instances into different classes, e.g. Maximum-Entropy based classifier, Support Vector Machine, or Example-based classifier etc.

Based on the observation that metaphor is a conceptual and semantic deviation rather than a grammatical one (MacCormac, 1985; Ricoeur, 1977), this paper follows the "Pragglejaz" metaphor identification procedure in Steen(2007) to construct a metaphor annotation corpus using subject-predicate constructions (abbreviated as subj-preds) in Chinese, examines the limitations of Selectional-Preference (abbreviated as SP) based model of metaphor recognition and proposes a new model for metaphor recognition which integrates various knowledge sources into a pattern named Semantic Relation Pattern (abbreviated as SRP) and makes use of support vector machine (SVM) for classification. Contrastive experiments between SP-based model and SRP-based model shows that the SRP-based model possesses many advantages over the SP-based model, which is of general use in the literature. In the experiments, the SRP-based model achieves an F1 of 89% in metaphor recognition, which is about 37% higher than that of the SP-based model, posing as a promising metaphor recognition model for subject-predicate construction and other endocentric constructions.

The paper is organized as follows. Section 2 reviews the literature on metaphor recognition, section 3 introduces the criteria used to identify metaphors in the paper, section 4 discusses the limitations of SP-Based model and the experiment results with the model, section 5 introduces the SRP-Based model of metaphor recognition, section 6 explains the contrastive experiments and analyzes the outcomes. The paper concludes with a discussion of the feasibility of generalizing the SRP-based model.

## 2 Related Work

In the literature of metaphor recognition, SP-Based model is the most widely adopted. The model relies on SP as knowledge source for metaphor recognition. An early SP-based metaphor recognition can be found in the Met* system(Fass, 1991) which is based on selection restriction and identifies metaphor as one type of violation of selection restriction. In CorMet(Mason, 2004), a language-domain based selection restriction is used to find metaphorical mappings and conventional metaphors. Lately, Baumer et al(2009) expands CorMet and apply the model of metaphor recognition in the domain of blogs. Gedigian et al(2006) uses verb frames from FrameNet to recognize verb metaphors. Jia et al(2008) also relies on Selectional Preference but additional source domain determination mechanism is used to improve the recognition precision. It reports a maximum F-1 of 90.07%.

As a similar concept to SP, collocation is also used in metaphor recognition. In Birke et al (2007), collocation is used to distinguish literal use and non-literal use of verbs.

Krishnakumaran et al (2007) relies on frequency of collocation to detect metaphors in the structure of "verb-noun" and "adj-noun". Yang(2008) conducts irregular collocation recognition of Chinese verb-obj constructions based on collocation deviation and reports a precision of 81.5% and a recall of 80.7%.

Contextual constraints constituted by the left and right neighbouring words are also used in metaphor recognition. This could also be considered as a relaxation on the concept of collocation, as some of the neighbours are actually collocations. This approach is generally coupled with machine-learning approaches. For instance, Wang et al(2006) uses word context to recognize "noun+noun" metaphors with Maximum Entropy. Pasanek(2008) and Jia(2010) also use contextual features in Support Vector Machines for metaphor recognition.

## 3 Metaphor Identification Criteria

As is pointed by many researchers, for example Searle(1979), Gibbs(1999) and Steen(2007), to conduct research on metaphor, an operational definition has to be given before any further discussion can be carried out. As metaphor is a semantic or conceptual deviation of the literal expression, a definition of metaphor can be established only after the definition of literality is given in advance. As such, Mason(2004) uses sub-domain corpus to define literality and thus metaphor, Searle(1979) employs truth condition for literal meaning specification and defines the expressions which violate truth conditions as metaphors. To give a definition on metaphor, Gibbs(1994:75) discusses five types of criteria for the judgment of literality: context-free literality, conventional literality, subject-matter literality, non-metaphorical literality and truth-conditional literality.

This paper follows the "Pragglejaz" metaphor identification procedure proposed by Steen(2007) to determine whether an expression is a literal expression, or a metonym, or a metaphor, with some modifications. The details are given below:

- The literal meaning is a description of the objective world, instead of the subjective concepts and ideas. For example, "山洪(flood) 爆发(erupts)" is literal while "(热情(enthusiasm) 爆发(erupts))" is metaphorical because "山洪" refers to the flood which belongs to the objective real word while "热情" is a subjective concept. This criterion is of first priority.
- The literal meaning is related to evocation of sense-motion concepts such as image, sight, feel, smell, taste and other more concrete words. Examples in the case are "目光(looks)冰冷(is cold)" and "河水(water in river)冰冷(is cold)", in which "目光(looks)冰冷(is cold)" is metaphorical and "河水(water in river)冰冷(is cold)" is literal, because the latter is more concrete and is directly related to human sense.
- The literal meaning is related to human bodily action. For example, "儿童(children)活泼(is active)" is regarded as literal and "形式(form)活泼(is active)" as metaphorical.
- The literal meaning appears earlier in etymology. Typical examples for this criterion are "骑士(rider)上马(get on horse)" and "项目(project)上马(get on horse)", in which the former is literal because the sense by "上马(get on horse)" expressed in the construction is more original than the latter.

Equipped with above criteria, 6200 subject-predicate collocations are extracted from a subject-predicate database with 70,434 subject-predicates and are annotated according to the working definition of metaphor given above to build the metaphor corpus, with tags for literal, metonymic or metaphorical. Some examples are given in Table 1. The senses are obtained using the algorithm in (Tang, Chen, Qu, & Yu, 2010).

| Index | Subj-head | Subj head sense | Pred-Head | Pred Head Sense | Type |
|---|---|---|---|---|---|
| 1 | 人 | [human\|人] | 潜伏 | [hide\|藏匿] | Literal |
| 2 | 蜘蛛 | [InsectWorm\|虫] | 潜伏 | [hide\|藏匿] | Literal |
| 3 | 病毒 | [software\|软件] | 潜伏 | [hide\|藏匿] | Metaphorical |
| 4 | 纵队 | [part\|部件:whole=[army\|军队]] | 潜伏 | [hide\|藏匿] | Metonymic |
| 5 | 部队 | [army\|军队] | 潜伏 | [hide\|藏匿] | Metonymic |

**Table 1. Subj-pred corpus format**

## 4 SP-Based Metaphor Recognition

### 4.1 Limitations of SP-based Metaphor Recognition

The model of SP-based metaphor recognition is based on the hypothesis that SP is isomorphic with semantic literality. In other words, if a construction satisfies the SP for a given word, it is interpreted as literal, otherwise it is not. For instance, Example 1(a) is interpreted as literal because the Chinese word "悲伤" literally means "be sad" and prefers "person" as its subject which is satisfied by the subject "病人(patient)". On the contrary, Example 1(b) and 1(c) deviate from the selection restriction "person be-sad" and form metonymy and metaphor respectively.

But the isomorphic hypothesis is challenged by conventional metaphor. Conventional metaphors are metaphors which have become conventional and entrenched in a linguistic community and may have probably entered dictionary as a word sense in the language. Example 2(b) is such an example:

**Example 2.**

(a)河水(river-water) 上涨(rises)

(b)工资(salary) 上涨(rises)

It can be seen that although example 2(b) is a typical example of selection restriction, it is more natural to consider 2(a) a literal expression and 2(b) a conventional metaphor. Otherwise the inner mechanism between the two usage of "上涨" is not specified.

The hypothesis is also challenged by some literal expressions which may not be considered as SP when computed statistically, such as 3(a). The verb "接近(be close to)" occurs 36 times in the corpus of 1998 January People's Daily (http://icl.pku.edu.cn/icl_groups/corpus/shengming.htm), wherein the verb occurs 8 times with subjects of concrete concept and 28 times with subjects of abstract concept. If SP is obtained via statistical co-occurrence, Example 3(a) will be wrongly regarded as deviation of SP while Example 3(b) is recognized as literal. This kind of judgment is surely against intuition.

**Example 3.**

(a) 飞机(plane) 接近(is close to) 塔楼(tower)

(b) 观点(opinions) 接近(are close)

Analysis on the above two types of linguistic expression shows that SP may not be taken as isomorphic with literality. Instead, the concept of literality is complex, judged with more than one criterion(Raymond W. Gibbs, Beitel, Harrington, & Sanders, 1994). At least, SP can not meet the working definition of metaphor given in this paper.

In addition, SP-based model of metaphor recognition is also constrained in its use in large-scale corpus, due to the fact that it is head idiosyncratic. SP varies with different predicate heads. For example, the verb "上涨(rise)" requires subjects within the semantic class of “water”, while “接近(be close to)” require physical objects or distance as subjects. Different heads possess different SP rules. Therefore, in SP-based model, particular SP rules are obtained and applied to recognized metaphorical use of particular heads, which may not be useful for other heads. Because of this constraint, researches of SP-based metaphor recognition, for example Jia et al(2008), often start with a list of words called metaphor word list, then proceed to construct SP knowledge for the words in the list and then recognize metaphorical use of head words specified within. The knowledge associated with the head words is difficult to be extended to recognize metaphorical use of words not in the list. For example, if SP rules are not given for the head “接近(be close to)” in a knowledge base, the model will not be used to recognize metaphors with the verb. Although semantic similarity can be used to obtain approximate SP rules(Yang, 2008), this kind of head idiosyncrasy is still a serious setback in open test where not all words can be included in the metaphor word list.

## 4.2 Experiments with SP-based Model

### *4.2.1 Data*

Experiments based on SP-based metaphor recognition model are conducted to further understand the limitations of SP-based model. The data used to obtain SP rules is the subject-predicate database mentioned before. A test corpus is obtained by taking 1586 subj-preds of 87 predicate heads from the metaphor corpus, which contains 810 literal subj-preds, 228 metonymic subj-preds and 548 metaphorical subj-preds.

### *4.2.2 Metaphor Recognition with SP-based Model*

The model of SP-based metaphor recognition used in the paper consists of two steps: acquisition of SPs and metaphor recognition. For instance, to determine whether Example 1(c), namely “天空(sky) 悲伤(is sad)”, is a metaphor, the association strength between “悲伤” and all its subjects, including “天空”, are firstly calculated. In the second step, a threshold of association strength is set and the association strength between “天空” and “悲伤” is compared to the threshold. If the association of the subj-pred is below threshold, it is recognized as a metaphor, otherwise it is not.

In the first step, the information-theoretic model(Resnik, 1996) is used to acquire SPs. Resnik(1996) defines two concepts: selectional preference strength(Formula 1) and selectional association (Formula 2), as are defined below:

$$S(p_i) = \sum_c \Pr(c \mid p_i) \log \frac{\Pr(c \mid p_i)}{\Pr(c)} \qquad (1)$$

$$A(p_i, c) = \frac{\Pr(c \mid p_i) \log \dfrac{\Pr(c \mid p_i)}{\Pr(c)}}{S(p_i)} \qquad (2)$$

wherein $\Pr(c \mid p_i)$ is the conditional probability of the semantic class c with condition of $p_i$, the predicate head, and $\Pr(c)$ is the probability of the semantic class c.

To obtain the threshold in the second step, the selectional association of the SPs for a given predicate head is normalized via formula 3:

$$\overline{A}(p_i, c) = \frac{A(p_i, c) - A_{\min}}{A_{\max} - A_{\min}} \quad (3)$$

where $A(p_i, c)$ is the selectional association between the predicate head $p_i$ and the subject head semantic class c, $A_{\min}$ and $A_{\max}$ are the minimum and maximum selectional association associated with the predicate head $p_i$. After normalization, the threshold $\theta$ is set via formula 4:

$$\theta = \frac{K}{10}, \; 0 < K \le 10 \quad (4)$$

where K is a variable between [1,9]. Once the threshold is set, metaphor recognition is performed by applying the following rule: for a pred-subj which has a normalized selectional association $\overline{A}$, if $\overline{A} < \theta$, it is metaphorical, otherwise it is not. Notice that different thresholds can be set when K moves from 1 to 9, indicating that a stronger selectional association is needed to be regarded as literal.

### *4.2.3 Experiment Analysis*

Figure 1 gives the F1 of metaphor recognition on test corpus for $1 \le k \le 9$ using SR-based model. The highest F-1 for metaphor recognition is 52.55% when K=1 and $\theta$=0.1, with a precision of 36.92% and a recall of 91.14%. The result is similar to the baseline reported in Jia et al(2008), which reports an F-1 of 65.38% on a smaller data. It can be seen that when K grows bigger, F1 decreases. The increase of K indicates the increase of selectional association and therefore the entrenchment of the construction. Subj-preds with stronger selectional associations are less likely to be metaphorical. As a result, the F-1 of metaphor recognition decreases. This fact adheres to the understanding that “Metaphor is a deviation of selectional preference”.

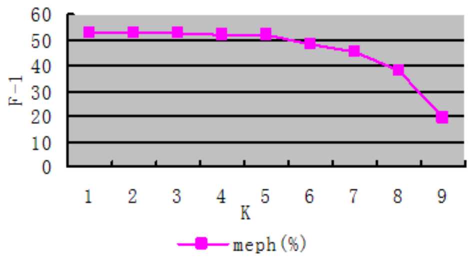


**Figure 1. F-1 of Metaphor in SP-based Model**

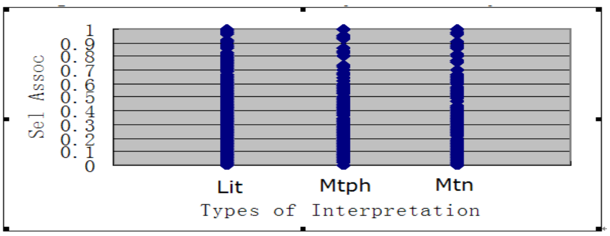


**Figure 2. Types of Interpretation and Selectional Associations. Lit for Literal, Mtph for Metaphorical and Mtn for metonymic.**

When K=1, the F1 is fairly low, due to the fact that the precision is just a mere 36.92%. This shows that the model often mistakes literal or metonymic subj-preds as metaphorical. An explanation can be found in Figure 2. Figure 2 is a scatter diagram of selectional associations for literal, metaphorical and metonymic subj-preds collected from the test corpus, in which coordinate X gives the three expression types and coordinate Y gives the selectional association. It can be seen that when selectional association is in the range of [0, 0.1], there exist not only metaphorical subj-preds, but also a large amount of literal and metonymic subj-preds. These literal and metonymic subj-preds are identified as metaphorical because their occurrences are not statistically significant enough to be taken as SP, as is explained in Example 3. In addition, Figure 2 also shows that there are metaphorical expressions possessing selectional associations above 0.75. These metaphorical expressions have strong selectional associations because they are conventional metaphors and are entrenched in the language, as is explained in Example 2. Thus it can be seen that the issue of metaphor recognition is not linearly separable for SP-based model. No matter how $\theta$ is set, there will be literal and metonymic constructions wrongly classified as metaphors, and metaphors not recognized.

## 5 SRP-Based Metaphor Recognition

The multiple-type literality requires that the knowledge sources used for metaphor recognition consists not just SP, but other types of semantic relations. It also asks for a model which can integrate different knowledge sources into a pattern so that a classifier can be applied to group linguistic construction into different categories. This section introduces the SRP-based Metaphor Recognition model which satisfies the above requirement.

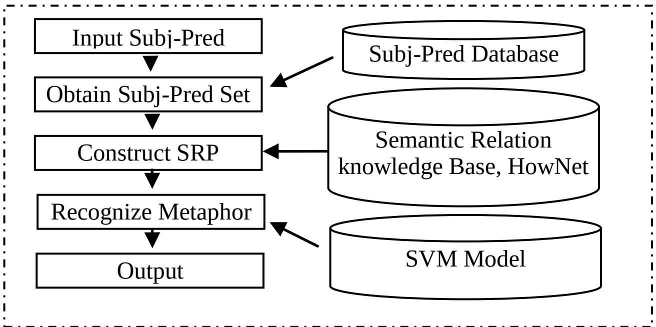


**Figure 3. SPR-based Metaphor Recognition Model**

This paper is focused on subject-predicate (subj-pred) constructions. Figure 3 illustrates the SRP-based model of metaphor recognition. Given a target subj-pred $< w_s$ ， $w_p >$, with predicate head $w_p$ and subject head $w_s$, the model firstly collects all subj-preds with $w_p$ as predicate head from the subj-pred database mentioned above. Then a SRP is constructed by considering the semantic relation types between the subject head $w_s$ in the target subj-pred and the subjects in the subj-pred set just obtained. The semantic relation is identified using a Sense-Relation Knowledge Database and HowNet(Dong, 2006). Thus metaphor recognition is transformed into a problem of pattern recognition based on SRP. A Support Vector Machine model is trained from training corpus and used for the purpose. For example, to recognize Example 1(c), the model firstly considers all the subj-preds with the adjective “悲

伤(be sad)" such as Example 1(a) and 1(b), and then analyzes different semantic relations between "天空(sky)" and other subject heads such as "病人(patient)", "全国(all over the country)" and "老人(old man)" etc. Then a SRP is constructed and used as input feature vector for the SVM classifier. The construction of SRP and Semantic Relation knowledge Base are explained in 5.1 and 5.2 separately. Metaphor recognition with SVM and experiment results are given in 5.3.

### 5.1 Semantic Relation Pattern

Given a subj-pred construction $c_i =< w_s^i, s_s^i, w_p^i, s_p^i >$ and the subj-pred set $\Gamma$ which has elements with the same predicate head word as $c_i$. The SRP of $c_i$ is the probability distribution of semantic relation types between the subject head $w_s^i$ and the heads of the subjects in $\Gamma$, defined as $\rho_c =< p(R_{mtph}^{\rightarrow}), p(R_{mtph}^{\leftarrow}), p(R_{mtn}^{\rightarrow}), p(R_{mtn}^{\leftarrow}), p(R_s), p(R_a) >$, where $p(R_{mtph}^{\rightarrow})$ is the distribution of conceptual metaphor source relation, $p(R_{mtph}^{\leftarrow})$ is the distribution of conceptual metaphor target relation, $p(R_{mtn}^{\leftarrow})$ is the distribution of conceptual metonymy target relation, $p(R_{mtn}^{\rightarrow})$ is conceptual metonymy source relation, $p(R_s)$ is semantic similarity relation and $p(R_a)$ is the distribution of semantic association relation.

| Subj-pred | $R_{mtph}^{\rightarrow}$ | $R_{mtph}^{\leftarrow}$ | $R_{mtn}^{\rightarrow}$ | $R_{mtn}^{\leftarrow}$ | $R_s$ | $R_a$ |
|---|---|---|---|---|---|---|
| 病人(patient)悲伤(is sad) | 0.33 | 0.0 | 0.00 | 0.33 | 0.33 | 0.33 |

**Table 2. Example for Semantic Relation Pattern**

Table 2 gives the SRP for Example 1(a) against the subj-pred set $\Gamma$ which consists of the other three subj-preds in Example 1. The distributions of $p(R_{mtph}^{\rightarrow})$ and $p(R_{mtph}^{\leftarrow})$ are firstly considered. Between 1(a) and 1(c) is a conceptual metaphor "[sky|空域] IS [human|人]", which can be detected by search for possible matches in the Semantic Relation Knowledge Base. Thus the subject "病人" in 1(a) forms 1 occurrence of conceptual metaphor source relation (namely $R_{mtph}^{\rightarrow}$) with the subject "天空" in 1(c). No other conceptual metaphors can be found between 1(a) and 1(b) or 1(a) and 1(d). Formula 5 and Formula 6 explains how the two distributions are calculated:

$$p(R_{mtph}^{\rightarrow}) = Count(mtph(s_{subj}^i, s_{subj}^j)) / N \quad (5)$$

$$p(R_{mtph}^{\leftarrow}) = Count(mtph(s_{subj}^j, s_{subj}^i)) / N \quad (6)$$

Where $s_{subj}^i$ is the subject of the subj-pred in question, which is Example 1(a) in this case, $s_{subj}^j$ is the subject of one subj-pred in $\Gamma$. $mtph(X,Y)$ is a conceptual metaphor, which has X as the source domain, and Y the target domain, N is the number of subj-preds in $\Gamma$. As such, $p(R_{mtph}^{\rightarrow})$ =1/3=0.33. As for the distribution $p(R_{mtph}^{\leftarrow})$, because there's no conceptual metaphor is found in which the subject in 1(a) can serve as the target, $p(R_{mtph}^{\leftarrow})$ = 0/3=0. Notice that $p(R_{mtph}^{\rightarrow})$ and $p(R_{mtph}^{\leftarrow})$ are directed.

Then the distribution of $p(R_{mtn}^{\rightarrow})$ and $p(R_{mtn}^{\leftarrow})$ for Example 1(a) can be considered. Between 1(a) and 1(b) there is a metonymy "[human|人] IS [place|地方]", where "[place|地

方]" is the source and "[human|人]" is the target. This is also detected by searching for possible matches in the Semantic Relation Knowledge Database. Thus the subject in 1(a) forms 1 conceptual metonymy target relation (namely $R_{mtn}^{\leftarrow}$) with the subject "全国" in 1(b). Accordingly, these two distributions can be calculated by Formula 7 and 8:

$$p(R_{mtn}^{\rightarrow}) = Count(mtn(s_{subj}^{i}, s_{subj}^{j})) / N \tag{7}$$

$$p(R_{mtn}^{\leftarrow}) = Count(mtn(s_{subj}^{j}, s_{subj}^{i})) / N \tag{8}$$

Where $s_{subj}^{i}$ is the subject of the subj-pred in question, $s_{subj}^{j}$ is the subject of one subj-pred in $\Gamma$, $mtn(X, X)$ is the conceptual metonymy in which X is the source domain and Y is the target domain and N is the number of subj-preds in $\Gamma$. Thus in the present case, $p(R_{mtn}^{\leftarrow})$ =1/3=0.33 and $p(R_{mtn}^{\rightarrow})$ =0. These two relation types are also directed.

The distribution of $p(R_s)$ and $p(R_a)$ are concerned with the semantic similarity and semantic relevance between subject of Example 1(a) and subjects of subj-preds in $\Gamma$. These two distributions are calculated with following formulas:

$$p(R_s) = \sum sim(s_{subj}^{i}, s_{subj}^{j}) / N \tag{9}$$

$$p(R_a) = Count(rel(s_{subj}^{j}, s_{subj}^{i})) / N \tag{10}$$

Where $sim(s_{subj}^{i}, s_{subj}^{i})$ is the semantic similarity between $s_{subj}^{i}$, the subject of the subj-pred in question and $s_{subj}^{j}$, the subject of one subj-pred in $\Gamma$ and $rel(s_{subj}^{j}, s_{subj}^{i})$ is the semantic relevance between $s_{subj}^{i}$ and $s_{subj}^{j}$. Two methods are used to identify semantic similarity relation. One is based on the Semantic Relation Knowledge Database. The other is via the method described in Liu et al(2002). Similarly, two methods are used to identify semantic relevance, One is via the method described in Dong et al(2003), the other is based on the Semantic Relation Knowledge Database. In Table II, the Semantic-Relation-Knowledge-Database method is used. Between Example 1(a) and 1(d), the semantic similarity between "病人(patient)" and "老人(old man)" is obvious. Between 1(a) and 1(b), there is a semantic relevance between "病人(old man)" and "全国(all over the country)". Accordingly $p(R_s)$ =1/3=0.33 and $p(R_a)$ =1/3=0.33.

### 5.2 Construction of Semantic Relation Knowledge Database

In Section 5.1 above, it can be seen that the building of SRP for a subj-pred relies heavily on Semantic Relation Knowledge Database. In fact, Semantic Relation Knowledge Database is a crucial component in SRP-based Metaphor recognition. In this paper, the Semantic Relation Knowledge Database is automatically constructed from the metaphor corpus mentioned in Section 3. The method is explained below.

Consider two subj-preds $c_i =< w_s^i, s_s^i, w_p, s_p^i >$ and $c_j =< w_s^j, s_s^j, w_p, s_p^j >$, $c_i$ and $c_j$ have the same predicate head $w_p$. According to annotation in the corpus, $c_i$ has semantic expression type $t_i$ and $c_j$ has $t_j$. Subj-preds in Table I can be used for illustration, in which all the three subj-preds share the same predicate "潜伏(hide)". The following statements shall hold for $c_i$ and $c_j$:

(i) If $t_i$ is literal and $t_j$ is metaphorical, add $s_s^i \rightarrow s_s^j$ to knowledge database as a conceptual metaphor, in which $s_s^i$ is the source domain and $s_s^j$ is the target domain. For example, if $c_i$=<人, [human|人], 潜伏, [hide|藏匿]> and $c_j$=<病毒,[software|软件], 潜伏, [hide|藏匿]>, a conceptual metaphor "[software|软件] is [human|人]" can be obtained.

(ii) If $t_i$ is literal and $t_j$ is metonymic, add $s_s^j \rightarrow s_s^i$ as a conceptual metonymy, in which $s_s^j$ is the source domain and $s_s^i$ is the target domain. For example, if $c_i$=<人, [human|人], 潜伏, [hide|藏匿]> and $c_j$=<纵队,[part|部件], 潜伏, [hide|藏匿]>, a conceptual metonymy "[human|人] is [part|部件]" can be obtained.

(iii) If $t_i$ is literal and $t_j$ is also literal and $s_p^i = s_p^j$, $s_s^i$ relates to $s_s^j$ in semantic similarity. For example, if $c_i$=<人, [human|人], 潜伏, [hide|藏匿]> and $c_j$=<蜘蛛,[InsectWorm|虫], 潜伏, [hide|藏匿]>, "[human|人]" and "[InsectWorm|虫]" forms a relation of similarity.

(iv) If $t_i$ is metonymic and $t_j$ is also metonymic and $s_p^i = s_p^j$, $s_s^i$ relates to $s_s^j$ in semantic relevance. For example, if $c_i$=<纵队, [part|部件], 潜伏, [hide|藏匿]> and $c_j$=<部队,[ army|军队], 潜伏, [hide|藏匿]>, "[human|人]" and "[InsectWorm|虫]" forms a relation of semantic relevance.

Then the metaphor corpus is divided into clusters. In each cluster, the subj-preds share the same predicate head. By considering pair-wisely the subj-preds in each cluster and following the statements above, different types of semantic relations can be obtained to construct knowledge database.

### 5.3 Metaphor Recognition with SRP-Based Model

Once the SRP for a given subj-pred is constructed, the task of metaphor recognition is transformed into a problem of classification. A classifier can take in the SRP and decide what kind of expression the associated subj-pred is. This paper has adopted Support Vector Machine as the classifier and uses libSVM(Chang & Lin, 2001) as SVM training platform and chooses Radial Basis Function as the kernel function. To compare the experiment results with SP-Based model, the same test corpus is used as in SP-Based model. The rest part of metaphor corpus mentioned in Section 3 is used as training corpus. Thus a classifier model can be trained using the SRPs in the training corpus and libSVM, and then is applied on the test corpus for metaphor recognition. The training corpus contains 4614 subj-preds, among which are 2592 literal expressions, 1565 metaphors and 457 metonymies. It should be noted that the subj-preds in training corpus do not share any predicate head with the subj-preds in the test corpus. The metaphor corpus is deliberately divided in this manner to test the generalizing capacity of SRP-Based model.

From the procedure discussed above, it can be seen that the experiment results will be influenced by three factors. Two factors are associated with SVM training: parameter C for soft hyper-plane modification and parameter $\gamma$ in Radial Basis Function. These two factors are dealt with inside libSVM by cross experiments. The third factor is the scale of semantic relation knowledge database which determines the values inside the SRPs. This factor is further discussed in the following sections. The experiments also show that this is a crucial factor in SRP-Based Model.

#### *5.3.1 Experiment Data and Strategies*

In order to observe the influence of knowledge database scale on the recognition precision, three strategies are used to obtain the knowledge database, as follows.

Training-Corpus(TC) Strategy is the first employed strategy. Strategy A uses only the training corpus to construct semantic relation knowledge database. The SRP data format for training in this strategy is given in Table 3. The literal expression (No.1) has a high distribution in $R_{mtph}^{\rightarrow}$, which is a distinctive feature for literal expression; the metaphor (No. 2) does not have a distinctive feature yet, due to the fact no relevant conceptual metaphor can be found in the Semantic Relation Database; The metonym (No. 3) has a distinctive feature in $R_{mtn}^{\rightarrow}$, indicating that the subject "目光(look)" is used as a conceptual metaphor source. In the training process, it is found that the SVM model in this strategy achieves the best performance when C is in [0, 2] and $\gamma$ is in [0, 2].

| **Index** | **Subj-pred** | **Type** | $R_{mtph}^{\rightarrow}$ | $R_{mtph}^{\leftarrow}$ | $R_{mtn}^{\leftarrow}$ | $R_{mtn}^{\rightarrow}$ | $R_s$ | $R_a$ |
|---|---|---|---|---|---|---|---|---|
| 1 | 画卷(painting)展开(unfolds) | Lit | 0.45 | 0.02 | 0.04 | 0.00 | 0.22 | 0.16 |
| 2 | 训练(training)展开(unfolds) | Mtph | 0.00 | 0.00 | 0.00 | 0.14 | 0.37 | 0.04 |
| 3 | 目光(look)关注(focuses) | Mtn | 0.48 | 0.53 | 0.00 | 0.60 | 0.60 | 0.47 |

**Table 3. SRP Data Format in Strategy TC**

| **Index** | **Subj-pred** | **Type** | $R_{mtph}^{\rightarrow}$ | $R_{mtph}^{\leftarrow}$ | $R_{mtn}^{\leftarrow}$ | $R_{mtn}^{\rightarrow}$ | $R_s$ | $R_a$ |
|---|---|---|---|---|---|---|---|---|
| 1 | 画卷(painting)展开(unfolds) | Lit | 0.90 | 0.02 | 0.16 | 0.00 | 0.37 | 0.18 |
| 2 | 训练(training)展开(unfolds) | Mtph | 0.00 | 0.26 | 0.00 | 0.14 | 0.37 | 0.04 |
| 3 | 目光(look)关注(focuses) | Mtn | 0.48 | 0.53 | 0.00 | 0.67 | 0.60 | 0.80 |

**Table 4. SRP Data Format in Strategy AC**

| **Index** | **Subj-pred** | **T** | $R_{mtph}^{\rightarrow}$ | $R_{mtph}^{\leftarrow}$ | $R_{mtn}^{\leftarrow}$ | $R_{mtn}^{\rightarrow}$ | $R_s$ | $R_a$ | $R_s^{'}$ | $R_a^{'}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 画卷(painting)展开(unfolds) | Lit | 0.90 | 0.02 | 0.16 | 0.00 | 0.37 | 0.18 | 0.00 | 0.02 |
| 2 | 训练(training)展开(unfolds) | Mtph | 0.00 | 0.26 | 0.00 | 0.14 | 0.37 | 0.04 | 0.01 | 0.00 |
| 3 | 目光(look)关注(focuses) | Mtn | 0.48 | 0.53 | 0.00 | 0.67 | 0.60 | 0.80 | 0.02 | 0.00 |

**Table 5. SRP Data Format in Strategy CPH**

The second strategy is All-Corpus(AC) strategy. This strategy uses both training corpus and test corpus to obtain the knowledge database. The SRP data format is given in Table 4. Compared to Table 3, it can be seen that several values have changed. Particularly the change of feature for No. 2 is obvious in $R_{mtph}^{\leftarrow}$, which is important in correctly determining its type. This increase is due to the enlargement of Semantic Relation Knowledge Database. At the same time, the $R_{mtph}^{\rightarrow}$ for No. 1 is also obvious. In training, the SVM model achieves the best performance when C is in [0, 2] and $\gamma$ is in [1, 32].

The third strategy is called Corpus-Plus-HowNet(CPH) strategy, which uses not only the training corpus and test corpus for knowledge database construction, but also knowledge from HowNet: semantic similarity computation (Liu et al, 2002) and semantic relevance computation(Dong et al, 2003) within HowNet. The SRP data format is illustrated in Table 5, where $R_s^{'}$ and $R_a^{'}$ are the subsidiary data from HowNet. In this strategy, the SVM model also achieves the best performance when C is in [0, 2] and $\gamma$ is in [1, 32].

Table 6 illustrates the different knowledge database scales obtained in TC and AC strategies. It can be seen that the number of conceptual metaphors in AC strategy is about the double size of that in TC strategy, but the increase of other semantic relation types is not obvious.

| Strategy | $R^{\rightarrow}_{mtph}$ | $R^{\leftarrow}_{mtph}$ | $R^{\rightarrow}_{mtn}$ | $R^{\leftarrow}_{mtn}$ | $R_s$ | $R_a$ |
|---|---|---|---|---|---|---|
| TC | 5776 | 5776 | 1236 | 1236 | 17401 | 1778 |
| AC | 9036 | 9036 | 1508 | 1508 | 18222 | 2145 |

**Table 6. Knowledge Scale in Strategy TC and AC**

### *5.3.2 Experiment Analysis*

Table 7 gives the Precision(P), Recall(R), and F-1 for the recognition of literality, metaphor and metonymy in Strategy TC, AC and CPH. The F-1 value can be compared to (Jia & Yu, 2008) which reports an F-1 of 90.07% on 413 sentences and is higher than (杨芸, 2008). Notice that the test data contains 1586 subj-preds.

| Strategy | Literality(%) | | | Metaphor(%) | | | Metonymy(%) | | |
|---|---|---|---|---|---|---|---|---|---|
| | ***P*** | ***R*** | ***F-1*** | ***P*** | ***R*** | ***F-1*** | ***P*** | ***R*** | ***F-1*** |
| TC | 74.17 | 86.28 | 79.77 | **74.74** | **80.47** | **77.50** | 62.96 | 14.91 | 24.11 |
| AC | 81.59 | 93.2 | 87.22 | **89.04** | **85.94** | **87.46** | 83.09 | 49.56 | 62.09 |
| CPH | 81.35 | 96.54 | 88.30 | **94.41** | **84.67** | **89.15** | 81.06 | 46.92 | 59.44 |

**Table 7. Experiments Result for SRP-based model[1]**

The role of knowledge scale can be easily seen in the analysis of the recognition results. Strategy TC has the lowest F-1 because only the training corpus is used for the acquisition of the knowledge database of semantic resources. Strategy AC has an improved F-1 as both the training data and the test data are used for knowledge acquisition. Strategy C has the highest F-1 in metaphor recognition by coupling subsidiary semantic relation knowledge from HowNet. It can thus be safely concluded that the more sufficient knowledge of semantic relations the model possesses, the better the performance it shall achieve.

Metaphor recognition results in Table 7 also show that in SRP-based model, the recall is lower than precision. Detailed analysis on the recognition results in Strategy CPH shows that the metaphors not successfully recognized possess the following two features: (1) the subject heads are often used as source domains in conceptual metaphors; (2) the predicate heads have strong SP. In the experiment, 50 out of 105 unsuccessfully recognized metaphors have concrete concepts as their subject heads. For example, "黑枪(smuggled guns)流入(flow in)", "羊羔(lambs)嬉戏(romp)", "动物(Animals)亲近(are intimate)" and "大浪(Big wave)吞噬(swallows)" etc. These examples also illustrate the second feature: their predicate heads have strong Selectional Preference. The predicates "嬉戏(romp)", "亲近(be intimate)" requires human as subjects, "流入(flow)" requires liquid and "吞噬(swallow)" requires certain types of animals such as snake and whales etc. How to account for these metaphors within SRP-based model is a topic in future research.

## 6 Contrastive Analysis

Contrast between Table VII and Figure 1 shows that SRP-based model outperforms SP-based model to a great extent. Strategy TC is 25% higher and Strategy CPH is 37% higher in F1 than the SP-based model. Several factors have contributed to the improved performance of SRP-based models.

[1] Different C and $\gamma$ are used to obtain the result in the table. In Strategy A, C=0.1, $\gamma$ =1.5. In Strategy B, C=2, $\gamma$ =2.5. In Strategy C, C=1 and $\gamma$ =2.5

One factor is that SRP distinguishes conventional metaphors from literal constructions which SP often fails to. Among the 200 metaphors correctly identified in Strategy C but failed with SP, most of them are conventional metaphors (Example 4). The introduction of

**Example 4.**

| | |
|---|---|
| (a) 恶名(notoriety) | 洗刷(rinsed) |
| (b)雷达(radar) | 寻觅(seeks) |
| (c)冷战(cold-war) | 展开(unfolds) |
| (d)野心(ambition) | 大(is big) |
| (d)买卖(business) | 停滞(stops) |

conceptual metaphor as knowledge source into SRP is crucial for the correct identification. This can be seen in the value of $p(R^{\rightarrow}_{mtph})$ and $p(R^{\leftarrow}_{mtph})$ in Table 5. For the subj-pred "画卷(painting)展开(unfolds)", the value of $p(R^{\rightarrow}_{mtph})$ is 0.90 while the value of $p(R^{\leftarrow}_{mtph})$ is 0.00. For the subj-pred "训练(training)展开(unfolds), the value of $p(R^{\rightarrow}_{mtph})$ is 0.00 while the value of $p(R^{\leftarrow}_{mtph})$ is 0.26. The distinction between the two SPRs is obvious.

| Subj-red | T | $R^{\rightarrow}_{mtph}$ | $R^{\leftarrow}_{mtph}$ | $R^{\rightarrow}_{mtn}$ | $R^{\leftarrow}_{mtn}$ | $R_s$ | $R_a$ | $R'_s$ | $R'_a$ |
|---|---|---|---|---|---|---|---|---|---|
| 幼苗扎根 | Lit | 0.50 | 0.50 | 0.00 | 0.00 | 0.50 | 0.50 | 0.34 | 0.00 |
| 舞台坍塌 | Lit | 0.75 | 0.76 | 0.70 | 0.70 | 0.78 | 0.92 | 0.00 | 0.20 |

**Table 8. SRPs for "幼芽扎根" and "舞台坍塌"**

Another factor is that SRP is able to identify those literal expressions that do not have strong selectional associations. There are more than 300 literal expressions that are correctly identified in Strategy CPH but are failed with SP, as is in Example 5.

**Example 5**

| | |
|---|---|
| (a)舞台(stage) | 坍塌(collapses) |
| (b)部下(underling) | 投降 (surrenders) |
| (c)血液(blood) | 吸收(absorbs) |
| (d)幼芽(plumule) | 扎根(roots) |

These expressions have low selectional associations due to data sparseness in the corpus used for SP acquisition. The predicate head "坍塌(collapses)" and "扎根(root)" both have only two samples in the SP acquisition corpus. But by SRP, the features that are crucial for correct recognition are explicitly unveiled for classifier. Table 8 gives the SRP for Example 5(a) and 5(d). The features of $R^{\rightarrow}_{mtph}$, $R_s$, $R_a$, $R'_s$ and $R'_a$ are all possible clues for the identifying the constructions as literal, which are not accounted for in SP model.

As is discussed in Section 4.1, in SP-based model, the SPs are head-idiosyncratic, determined by predicate heads. Predicate heads not found in SP database often provoke the problem of knowledge shortage. However, this constraint can be overcome by SRP-Based model. In Section 5.3 it is mentioned that the training corpus used for building SVM model does not share predicate heads with the test corpus and the construction of SRP is based on semantic relation database and collocation clusters. SRP-based model relies on SRP for metaphor recognition. As is illustrated above, SRP is a pattern consists of a vector of real numbers which is obtained by resorting to sense relation knowledge database which is not head-idiosyncratic. The SVM classifier is also not head-idiosyncratic. If a subj-pred with a certain SRP is identified as a metaphor, as in the case of "训练(training)展开(unfolds)", it should be safe to conclude that other subj-preds with similar SRP are also metaphors. This nature of SRP makes it possible for the pattern obtained in one Subj-Pred Cluster to be applicable in other Subj-Pred Clusters, even though the predicte heads have not been known before. Thus the concept of metaphor characterized in SRP-based model is general, not associated to any particular predicate head and approximate more closely the concept of metaphor possessed by human. This observation is testified by the fact that Strategy TC achieves a fairly satisfactory F-1 with a small training data and very limited knowledge source. Accordingly, SRP-based model do not rely on metaphor word list as SP-Based model does, because of its power to generalize to unknown predicate heads. This feature enables SRP-based model to identify metaphors in large scale corpus.

## 7 Conclusion

Metaphor recognition is the first step in metaphor understanding. Most researches reported in metaphor recognition literature have chosen SP as the major knowledge source. However, the role assigned to SP in metaphor recognition is problematic because literality types based on truth-condition literality, conventional metaphors and other SP violations can not be accounted for with SP. In this paper, a new model of metaphor recognition, named SRP-based metaphor recognition is proposed in the paper . The model firstly constructs a SRP within a Subj-Pred Cluster, which integrates different semantic relations within the cluster, and then employs SVM to perform the classification. Contrastive experiments show that SP-based model can obtain an F-1 of 52% in metaphor recognition, while SRP-based model achieves an F-1 of 89% in the same test set. Analysis on the experiment result shows that SRP-based model better explains conventional metaphor, truth-condition literality and other types of literality and metaphor. It also shows that SRP-based model has the ability to generalize to those predicate heads that are not known before and approximate more closely the concept of metaphor possessed by human.

Although this paper is focused on the recognition of subj-pred constructions, it is believed that SRP-based metaphor should be applicable to other endocentric constructions such as verb-objects and adjective-nouns. According to Section 5.1, the construction cluster is based on the head of the construction and the SRP is based on the complement of the construction. Thus in verb-objects, the verb will be used to construct construction clusters and the object head will be used to construct SRPs, while in adjective-nouns, the adjective will be used for cluster construction and the noun will be used for SRP construction. Thus SRP-based model can be used to recognize metaphors in these constructions.

## 8 Acknowledgement

This work is supported by Chinese National Science Fund under Grant 60773173 and 61073119, and Chinese National Fund of Social Science under Grant 07BYY050 and 10CYY021. We are also grateful to the autonomous reviewers for their valuable advice and suggestions.

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