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Metaphor Detection: Leveraging Culturally Grounded Eventive Information

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ABSTRACT Metaphors are compact packages of information with rich cultural background information. As one of the most powerful linguistic forms with non-literal meaning, metaphor detection in natural language processing can be both challenging and rewarding. We propose an innovative method for metaphor detection and classification leveraging culturally grounded eventive information. This culturally grounded information is organized based on ontological structure, which in turn facilitates further semantic processing of the result of our classification. As a culturally bound ontological system, the Chinese writing system has basic concepts organized according to semantic radicals, which are symbols containing rich eventive information that represent categorical concepts. This paper illustrates the basic design principles of applying ontological structures in metaphor detection by taking into account radicals representing body parts, instruments, materials, and movements. Our approach to leverage the eventive information of the Chinese writing system in metaphor detection is based on the fact that such information is available as an integral part of the writing system of any text. We hypothesize that eventive information can be accessed through the ‘‘embodied’’ source domain information represented by the radicals without syntactic processing or annotation. In terms of the theory of metaphor, we further hypothesize that eventive types in the embodied source domain maps to, and hence can help to predict, eventive meaning in the target domain of metaphor. Our studies show that the event information encoded in lexical items can facilitate classification of metaphoric events and identification of metaphors in Chinese texts effectively. We achieved improvements in Chinese metaphor detection over state-of-the-art approaches in our first classification experiment, and our proposed approach is shown to be generalizable in a second experiment involving new sets of characters with the same radicals.

INDEX TERMS Metaphor detection, Chinese radicals, ontology, eventive information, writing system.

I. INTRODUCTION

Metaphors are compact packages of information with rich cultural background information. As one of the most powerful linguistic forms with non-literal meaning, metaphor detection in natural language processing can be both challenging and rewarding. We propose an innovative method for metaphor detection and classification through leveraging culturally grounded eventive information. This culturally grounded information is organized based on onto- logical structure [1]. The adoption of ontology as a representation of eventive structure is crucial as it provides foundation for future semantic processing [1]. which allows application based on the event structures [2], [3]. Event structures, which are encoded in constructions and frames, have been shown to be effective in metaphor detection [4]. From the point of view that radicals are sub-lexical constructions, our approach focuses on incorporating event structures in the task of metaphor detection in Chinese datasets. Our proposal relies crucially on the fact that the Chinese writing system can be viewed as an ontological system based on the conceptual classes defined and formed by radicals as basic components of characters [5]. As basic unit of the writing system, each character typically contains a single semantic radical which represents a basic concept shared by all characters with that radical. Hence, the eventive information encoded in radicals is accessible in all Chinese texts as well as Chinese characters (or kanji) texts in all languages that still use them, including Japanese and Korean [6]. In this way, the ontological system of Chinese characters can be treated as a kind of linguistic ontology, which is similar to the use of wordnets as linguistic ontologies to be linked to formal ontologies [7]. Chinese orthography contains a wide variety of pictographs and ideographs, which represents our actions, perceptions, and experiences in the world. As pointed out in [6], many aspects of cognition are grounded in embodiment, which is an essential part of the cognitive processes which human beings use to make sense of their experiences in the world. Importantly, Chinese radicals are a type of embodiment. The radicals not only represent bodily experience but also encode event types. The employment of information from orthography contributes to culturally relevant background information for the task of metaphor detection. [8].

A wide array of corpus linguistic and experimental studies have shown that conceptual metaphors occur in everyday language cross-linguistically [9], [10]. Since metaphors occur pervasively in all kinds of texts, a great amount of studies in the natural language processing focus on detecting whether a linguistic expression is a metaphoric sense or not. Hence the main goal of the task of metaphor detection is to distinguish metaphoric senses from literal senses in a target text. The majority of previous NLP work on metaphor detection takes a lexical semantic perspective by using patterns of co-occurrences of neighboring word to differentiate metaphoric meanings as metaphoric usages and literal usages will have collocations with different meanings [11]. However, contextual information is not always reliable since it is indirect evidence and the metaphoric usages inevitably share some linguistic features of literal meaning.

The approach used in this study is different from the widely adopted lexical semantics-based perspective. In this study, the natural language processing techniques are applied to leverage two deep culturally bound phenomena: the classification of metaphors and the Chinese writing system. Chinese metaphors follow general linguistic rules but also have their own culture- specific properties. Thus, analysis of metaphor should be approached in its cultural context [12], [13]. Since metaphors and Chinese radicals are both bound to cultures, the use of radicals can make the task of metaphor detection more effective and precise. This study provides an event types- based approach to identity and classify metaphors. Eventive information is inherent in the orthography of characters. Metaphors concern mappings of conceptual structures from a source domain to a target domain. The concepts can thus be classified into event types and then be applied to the classification of metaphors.

Previous metaphor detection literature dealt primarily with English texts; hence metaphor detection research in Chinese covered a narrow range of topics. These previous studies of metaphor identification mainly focus on adjectival and nominal phrases due to the rich contextual information of the two categories [14]. Indeed, the contextual information of verbs is more difficult to discover automatically, and thus metaphor detection of the verbs is done only sparsely regardless of the fact that they provide the foundation of eventive information [14]. Our experiments deal with the challenge by leveraging eventive information encoded in the Chinese writing system. It is argued that semantics is the orthographically relevant level in Chinese orthography [15], [16]. For example, the verb of eating 吃 *chi* contains the mouth-shape radical 口 *'mouth'*; the verb 推 *tui* 'push' has the hand-shape radical 扌 *'hand'*. In these examples, the body part radicals represent concept ranging from the body parts to their main functions. This generalization can be extended to radicals representing natural objects and artifacts. For instance, radicals can encode the concept of event of separation via representation of the tool. Examples include the radical 刀 *dao* 'nife' of the character 切 *qie* 'cut', an action resulting in the object being separated into two pieces, as well as the radical 石 *shi* 'tone' of the character 破 *po* 'break', an action resulting in the object breaking into pieces. These radicals can thus provide broad event types to identify the source domain in the task of metaphor detection. Additional eventive information, such as the volition of the subject and the resulted status of the object, can be accessed by their corresponding syntactic constructions. Thus, we propose a detailed set of syntactic features to be used as features to differentiate types of event via machine learning.

Figurative devices such as metaphors contain rich semantics, which is challenging for computational approaches to NLP to process cross-domain structure alignment [17]. On the other hand, literal senses are relatively easy to retrieve; hence Veale [17] propose a hybrid way of information retrieval and figurative language processing to increase the effectiveness of detecting metaphors. In this study, we also use the patterns of literal senses as basis to predict where a sense is used in its metaphoric sense. We hypothesize that sub-textual information encoded in radicals can improve the performance of identifying and classifying different types of metaphors in the Chinese text. In the first experiment, we implemented the eventive information in a machine learning model in order to increase the performance of metaphor detection. In the second experiment, we applied our model from the first phase to new lexical items to verify if the models can make generalizations. Results show that our proposed approach is especially effective for Chinese because of the information embedded in radicals. The same approach can also have broader implications in other languages by incorporating parsed eventive information in metaphor detection.

Related work in the natural language processing tasks of metaphor detection will be briefly reviewed in Section II. Section III introduces the connections between semantics-based orthography, event types, ontology, and the semantic distribution of metaphors. The two-phrase experiments will be detailed in Section IV and V. Section VI will discuss the results from the experiments and their implication; Section VII provides a brief conclusion.

II. LITERATURE REVIEW: AUTOMATIC METAPHOR DETECTION

Different NLP methods are used in metaphor detection, including clustering models [18]–[20], semantic similarity graphs [21], topic modeling [22], [23], and compositional distributional semantic models (CDSMs) [24]. Most of the methods primarily rely on contextual information to predict whether a targeted phrase is metaphoric [21], [25]–[30]. It is crucial to distinguish metaphoric senses from literal senses in a polysemy network in metaphor detection; therefore sense disambiguation is an essential step. Disambiguation of senses has been modeled by Distributional Semantic Models (DSMs) based on the availability of contextual information [31]–[34]. The more contextual information is incorporated; the more successful disambiguation would be. Notably, each sense of a polysemy has a different degree of transparency to be traced in semantics. It is much easier to deal with the senses of polysemy (cut a new window in the wall vs. the ball broke a window), which can be grouped together as each brings focus to a different aspect of the complex meaning and are compatible with each other. On the other hand, when the senses of a linguistic form are discrete as in the case of homonymy (e.g. piano keys vs. key point), it is a challenge to DSM [31]. It is suggested that the challenge arises from the lack of systematicity due to their highly context-dependent nature [24]. Given that the senses of polysemy form a system, it is argued that DSM has a better chance to detect metaphoric senses as a form of polysemy [24]. Similarly, how to group a variety of senses, including metonymic and metaphoric senses, has been a challenge in Chinese [14].

Previous studies on English rely on widely available re- sources, including both manually-tagged linguistic resources [35]–[37] and corpus-based approach [18], [26], [28], [38]. On the contrary, the only reported metaphor detection metaphor in Chinese is not yet easily accessible [39]. Regarding the verb category, Zhao *et al*. [40] use the contextual information to detect the metaphoric reading of 9 verb phrases based on collocation with noun phrases and point out that there is no mature syntactic and semantic tool for metaphor analysis in Chinese. Due to the limitation of available contextual information, it requires a lot of resources to extend to a larger number of verbs. Fu *et al*. [14] also rely on contextual information to develop hierarchical clustering for Chinese noun phrases in order to identify metaphoric phrases. Similarly, due to the constraints of available contextual information, their model can only cover a small set of nouns. To eliminate the reliance on contextual information in Chinese metaphor detection, Sun and Xie [41] propose an approach of extracting different types of sub-sequences of a sentence and claim that no external linguistic resources are needed. Although types of sub-sequences can contribute to the improvement of metaphor detection, the improvement is still limited.

In brief, our literature review points out the challenges and constraints in metaphor detection: the predication of metaphors relies mainly on contextual information, and thus previous studies focus on nominal and adjectival categories. In particular, there are even more limitations in Chinese due to the lack of reliable parsers for contextual information.

III. CHINESE RADICAL SYSTEM AS CULTURALLY BOUND ONTOLOGY

The advantages of radical-based analysis are the transparency of representation and bundling of different related senses in a polysemy. In addition, characters which contain the same radical overlap partially in semantics. Thus, we [42] pointed out that radicals serve as natural semantic classification and made the initial proposal as well as reported first attempt to leverage information from radicals for metaphor detection. This current paper incorporates this foundational study with replication and refinement to underline and explore the theoretical implications of this innovative approach. In particular, the current study incorporated the experiments reported in [41] but supplements them with more groups of characters. In particular, we propose to add an additional generalization experiment. The second phase experiment applies the result from the first experiment to characters sharing the same radical but not covered in the first experiment. By showing the generalizations based on radical groups can be extended to other characters from the same group, we will be able to out the unlikely possibility that the first study was a result of the idiosyncratic characteristics of the set of chosen characters. In what follows, we report the incorporated experiments holistically.

In the first phase experiment, 14 types of radicals are selected, as listed in Table 1. These radicals are chosen because each of them is the radical component of more high frequency verbs in Chinese Gigaword [43]. For example, verbs with the radical 扌 *shou* 'hand' indicate the action executed with hands; and verbs with the radical 刀 *dao* 'knife' refer to the action with the knife as an instrument.

In order to test how literal and metaphoric senses of a character differ in semantics, we use word embedding to show their semantic distribution. Word embedding represents a word through a low dimensional dense vector and has been widely used in lexicon-driven NLP tasks, such as semantic similarity, word analogy, word synonym detection, and concept categorization [31], [44]. Recent studies have employed embedding for contextual words [45] in order to distinguish metaphoric uses from literal uses [44]. We adopt word embedding not only for its proven effectiveness but also for the transparent approach that it offers to encode the context of potential metaphoric texts in terms of radicals. We conduct word embedding experiments to show how different concepts are categorized in terms of their semantic similarities. Based on this similarity, we can measure the semantic distance among groups of verbs with different radicals as well as the distance between the metaphoric and literal meanings of the same verb form.

Various models have been proposed to train the dense vector representation of words. They are all based on the

TABLE 1. Radical categories and sample characters.

Radical	火*huo* ‘fire’	水*shui* ‘water’	土*tu* ‘mud’	金 *jin* ‘gold’	石*shi* ‘stone’	刀*dao* ‘knife’	斤*jin* ‘ax’
Sample Characters	熬 *ao* ‘simmer’ 烤 *kao* ‘grill’	灌 *guan* ‘pour’ 沖 *chong* ‘flush’	墊 *dian* ‘pad’ 塞 *sai* ‘pack’	釘 *ding* ‘pin 鑽 *zuan* ‘drill’	砍 *kan* ‘chop’ 破 *po* ‘break 碰 *peng* ‘clash’	刷 *shua* ‘brush’ 切 *qie* ‘cut’	斬 *zan* ‘cut’ 斷 *duan* ‘snap’
Radical	糸*mi* ‘thread’	力 *li* ‘power’	扌*shou* ‘hand’	口 *kou* ‘mouth’	辶 *chou* ‘intermittent walk’	足*zu* ‘foot’	走*zou* ‘walk’
Sample Characters	綁 *bang* ‘tight’ 織 *zhi* ‘weave’	動 *dong* ‘move’ 加 *jia* ‘add’	抱 *bao* ‘hug’ 推 *tui* ‘push’	吃 *chi* ‘eat’ 咬 *yao* ‘bite’	逃 *tiao* ‘escape’ 追*zhui* ‘chase’	跳 *tiao* ‘jump’ 踢 *ti* ‘ kick’	走 *zou* ‘walk’ 趕 *gan* ‘chase’

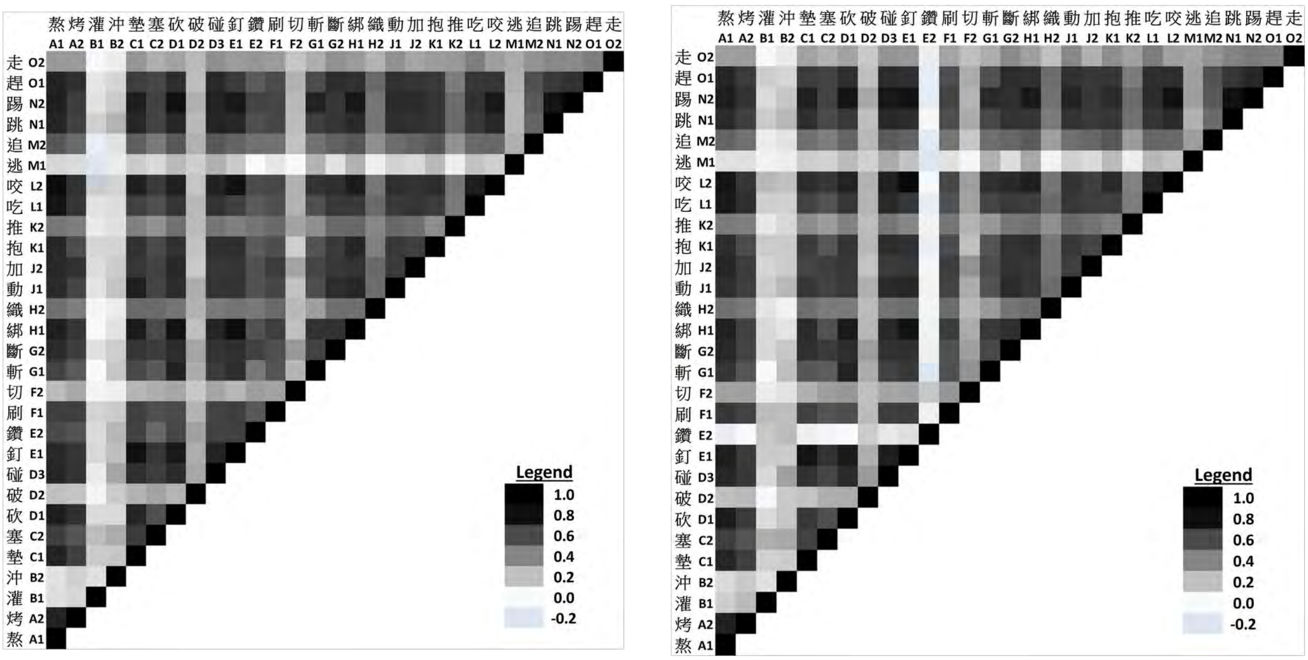

FIGURE 1. Semantic closeness among different verbs [left graph: literal sense; right graph: metaphoric sense].

hypothesis that words with similar meanings occur in similar contexts hence share distributional patterns [46]. The Skip-Gram model with negative sampling is widely used and will be adopted for our study [47]. Our word embedding representation is trained with default parameters from the Baidu Baike corpus[1] which is in turn word-segmented with the HIT LTP tool.[2]

Multi-dimensional vector space is used to show the distributional properties of the 29 selected verbs in terms of their literal senses and metaphoric senses respectively [31], [44]. The Support Vector Machine (SVM) classifier is applied to classify literal or metaphoric senses of each verb in Baidu Baike corpus, consisting of 1,543,669 entries and 7.6 billion tokens.[3] The semantic similarities among the 14 radical groups are then measured by the vector representation of each sense of each character in the group. The similarity of vectors based on word representation and sense representation shows that radicals can predict semantic groups of the literal senses. The graph on the left-hand side of Figure 1 shows that verbs having the same radical are relatively similar to each other compared to verbs which belong to different radical groups. However, as expected, the radical-based grouping does not predict the metaphoric senses very well, as shown in Figure 1 by the graph on the right. The sharp contrast supports the claim that the metaphoric senses of a verb have a different event structure from that of the literal senses.

The direct representation of conceptual classes by radicals allows us to leverage them to cluster similar concepts while minimizing the interference of homonymy [43]. Ontology-based approach has been applied to define the source domain of conceptual metaphors [48]. For example, the SUMO (Suggested Upper Merged Ontology)[4] is

[1] http://www.nlpcn.org/resource/
[2] http://www.ltp-cloud.com/
[3] *https : //en.wikipedia.org/wiki/Baidu*$_B$*aike*
[4] http://www.adampease.org/OP/

a shared upper ontology developed by the IEEE [2], [39]. It consists of approximately one thousand concepts, which are representations of shared human knowledge. The classification of concepts can help to account for the source-target pairing of concepts conceptual metaphors [43], [49]; thus SUMO is a good candidate for mapping information based on a priori source domains [49]. The previous studies use collocation in corpus to define the source domain based on the ontological structure. For instance, according to the corpus collocation with ECONOMY, the results can show that the frequent source domain is PERSON, BUILDING and COMPETITION. In general, this approach is still based on the contextual information.

The current study also uses ontology to detect metaphors, but with a different approach. Chinese radicals already clearly indicate source domain. In addition to the specification of source domain, each radical has its associated event types based on the organization of ontological structure. The eventive information can define a set of core syntactic constructions where literal senses of a verb tend to occur. When a sense does not fall in the set, it is very likely to be metaphoric. Our approach is more effective because it does not require resources to define source domains as in the previous studies.

IV. EVENT TYPES AND SYNTACTIC FEATURES

The semantic and ontological representation of a verb is an event structure [2], [49]. In addition, the perception of causality can also evoke the perception of metaphors [50]. We have shown that Chinese radicals represent the most profiled element in an event structure; hence the eventive information encoded by radicals can contribute to metaphors detection and classification. For example, 灌 *guan* 'pour', which has a water radical, has the literal meaning involving flow of water. Because of the conceptual prominence of dynamic flows, the verb tends to appear in non-passive constructions. The character 墊 *dian* 'pad', which has the mud radical 土 *tu*, profiles mud as a loctum to fill a space in its literal meaning. Hence it tends to appear with a locative phrase in order to specify the locus of filling. The character 切 *qie* 'cut', with the knife radical 刀, has the literal meaning of creation of separation with the specified instrument. The verb typically takes an object in the VO order as the target to be separated, as in 切菜 *qie cai* 'cut vegetables' with emphasis on transitivity. In short, the event structure of each verb can be observed based on the syntactic environments of the verb [46]. Since a metaphoric sense differs from its corresponding literal sense radically, we assume that their event structures and syntactic environments will also differ. We can further hypothesize that the metaphoric senses of a verb will deviate from the standard environments of its literal meaning. For instance, we observed that the metaphoric sense of 灌 *guan* 'pour' frequently appears in passive constructions, while its literal sense generally occurs in non-passive constructions. Similarly, the metaphoric sense of 墊 *dian* 'pad' is observed to occur frequently without a locative phrase, whereas the literal senses typically co-occur with one. The metaphoric sense of 切 *qie* 'cut' as in 'to severe the relationship' occurs frequently with the theme fronted, while the literal sense typically has the VO word order. The event types of literal and metaphoric senses of the same verb form are expected to differ since they are two different senses in two different conceptual domains. For instance, both the literal and metaphoric senses of 切 *qie* 'cut' refer to the concept of separation, but the separation occurs in different contexts. The literal meaning involves the separation of a concrete entity, while the metaphoric meaning involves to the discontinuation of a relationship. This change of event types entails differences in their grammatical contexts, which provides information for our prediction. We use the syntactic environments of the literal senses as the norm for comparison. When a usage involves a different set of syntactic features, it is most likely to belong a different sense, and possibly metaphoric. Since the word embedding in Section III show that the verbs with the same radical have similar distribution in literal senses, it is reasonable to assume that these radical groups will also be useful in prediction of behaviors involving meaning extensions.

In order to test the validity and effectiveness of radical based on metaphor detection, we first construct a distributional model with a set of syntactic features as cues for differences between the literal and metaphoric senses of the same verb form. These syntactic features are selected based on the distributional features of the literal senses of the 29 verbs. The 17 syntactic features are listed below for easy reference.

- Verb-Object Word Order (VO): For verbs taking an object, they may occur in either the VO or OV word order.
- Compounding (VV): For verbs forming a compound with another verb in VV form, we require that the target verb be the second one (i.e. occur in head position).
- Transitivity (Vt): The verb may be transitive or intransitive.
- Passive construction (Pass): The verb may occur in a passive construction, as marked by passive markers, such as 被 *bei*.
- Disposal constructions (Disposal): The verb may occur with the disposal markers to foreground the semantic patient or the direct object.
- Double-object construction (DO): The verb may take both a direct object and an indirect object.
- Relative clauses (RC): The verbs may occur with a relative clause. This feature is indicated by the relative clause markers 的 *de*..
- Numeral phrases (Num): Amounts relevant to the event are specified by numeral-classifier phrases.
- Locative phrases (Loc): Location of the event is specified by a locative phrase either before or after the verb.
- Negation (Neg): Negative markers appear in the main clause which contains the verb.
- Postpositions (Post): The verb may take a post-position phrase.
- Prepositions (Prep): The verb may occur with a preposition phrase. The indicators are the prepositions.

- Instrumental 用*yong* 'use' (yong): The instruments are profiled with this marker.
- Instrumental 對 *dui* 'to/ toward' (dui): The goal of the verb is profiled by this marker.
- Instrumental Beneficiary/ maleficent marker 給 *gei* (gei): The affectiveness of the event relevant to the target verb is specified.
- Postverbal adverbs (Vadv): The verb may be followed by an adverb which specifies degrees or durations of time.

The syntactic features are incorporated in both the first phase and the second phase experiments, which will be detailed in Section V V.

Based on the two principles, the syntactic features are divided into three groups, as listed below:

- Feature Group 1 (Features related directly to event types): transitivity (Vt), numeral phrases (Num), relative clauses(RC), compounding (VV), tense, word order (VO), and double-object construction (DO).
- Feature Group 2 (Feature related indirectly to event types): negation (Neg), prepositions (Prep), locative phrases (Loc), postverbal adverbial (Vadv), passivity (Pass), and aspectual markers (Asp).
- Feature Group 3 (Features pertaining to information structure): disposal constructions (Disposal), postpositions (Post), instrumental 用 *yong* 'use' (yong), dui 'to/toward' (dui), and beneficiary/maleficient marker *gei* (gei).

V. EVENT TYPE AND ONTOLOGY DRIVEN METAPHOR DETECTION

We conduct experiments of feature analysis to test the validity and effectiveness of the proposed features for metaphor detection. This section introduces the dataset used in the experiments as well as the procedure of the two-phase experiments.

A. DATA COLLECTION AND DATASET CONSTRUCTION

The experimental dataset is constructed using the 29 selected verbs introduced in Section III. These verbs each have a component radical from the 14 radicals chosen for study because of their clear embodied meaning, and coverage in character formation. A random sample of 200-300 sentences involving each verb is collected from the 1.1 billion character PoS tagged Chinese Gigaword corpus [43]. This corpus contains more than 700 million characters from Taiwan's Central News Agency, and close to 400 million characters from China's Xinhua News Agency. Two Chinese native- speaker annotators manually annotated the metaphoric and literal senses of each token based on Hantology [51], a Chinese character ontology with radical word composition information as well as SUMO conceptual class assigned to each sense of the character based on aggregated sense definition from several authoritative dictionaries. The inter- annotator agreement has kappa value of over 0.81 to support its consistency [52]. In total of the 6,047 tokens of the relevant dataset, 1,738 of them are labeled as a metaphoric sense and 4,309 are labeled as a literal sense.

B. EXPERIMENT 1: PROPOSED SYNTACTIC FEATURES IN A MACHINE LEARNING MODEL

The first experiment is machine learning of metaphor detection with the proposed syntactic features added to the feature set for implementation. We ran SVM classification algorithm on the dataset just introduced. SVM typically performs well in higher dimension, especially when targeted instances represent only a small portion of the dataset. Since our design focuses on the effectiveness of the syntactic features instead of the classifier, we choose SVM with linear kernel as our classifier for its linear binary classification and use LibSVM [48] as the SVM tool.

For baseline, we adopt two widely used word weighing schemes with unannotated text features in text mining problems. The first scheme is the bag-of-words approach, in which a text (such as a sentence or a document) is represented as the bag (multiset) of the words it contains, without grammar structure or word order information but with all duplicated words kept. This is the same baseline reported in [42]. The additional baseline involves term frequency and inverse document frequency (Tf-idf). Tf-idf is a numerical statistic that is intended to reflect how important a word is to a document in a collection or corpus. It is often used as a weighting factor in information retrieval, text mining, and user modeling. These two baselines make good prediction of state-of-the-art results.

The task of metaphor detection is modeled as a binary class classification of metaphoric vs. literal senses. 10-fold cross validation is performed to avoid over-fitting. The 17 features are divided into 3 feature groups for testing, defined based on two principles: (i) the probability of the occurrence of the metaphoric senses in the syntactic feature in question; (ii) the degree of clusters among the verbs. As shown in Figure 2, the metaphoric senses frequently occur in some syntactic features, such as Vt, VO, and relative clauses. In terms of the principle of the clusters, the syntactic feature which has fewer overlapping data points is more effective in distinguishing different senses.

Table 2 shows the results of inclusion of the features into the machine learning. The incorporation of all the 17 features outperforms the two baselines (bag-of-words and TFIDF) in F- score. Feature Group 1 in particular has the best performance, and when Feature Group 2 and Group 3 are added to the baseline respectively, they do not contribute to improving the model. In fact, Feature Group 3 lowers both Precision and Recall. Notably, while the model incorporates Group 1 to Group 3, the precision is improved at the expense of a slight decrease in recall. This increase in precision indicates that the features of Group 2 and Group 3 still contribute useful information to metaphor detection.

C. LITERAL AND METAPHORIC SENSES DEFINED BY SYNTACTIC FEATURES

Results from the first phase experiments show that the proposed syntactic features can improve metaphor detection. Seven of our proposed syntactic features: transitivity, relative clauses, double objects, word order, compounds, numeral

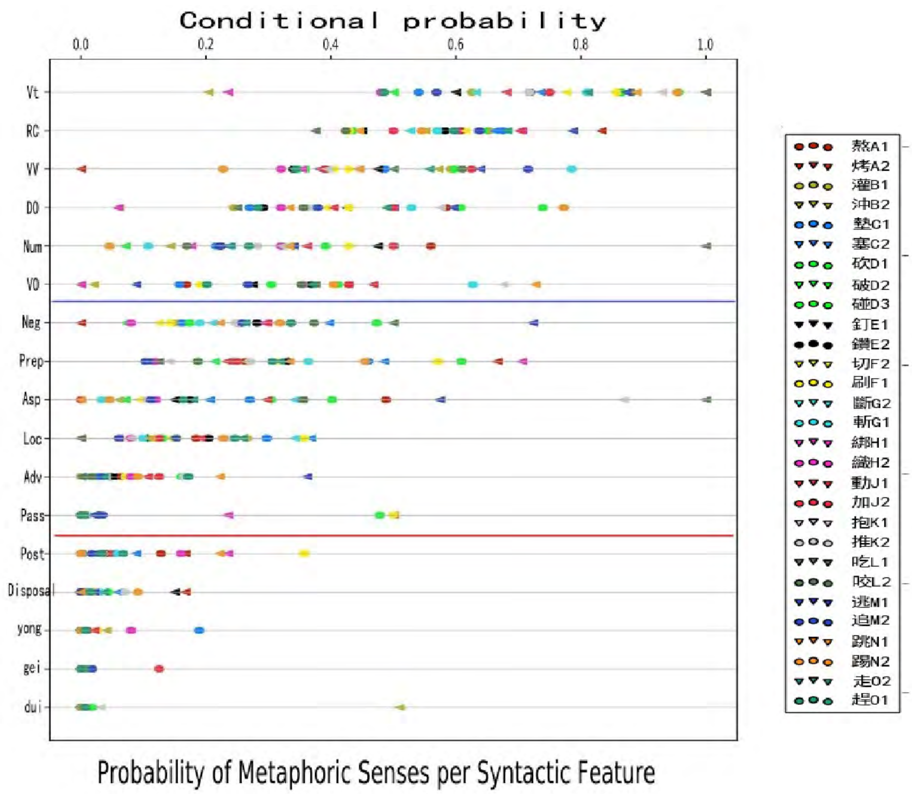

FIGURE 2. **Probability of metaphoric senses in each syntactic feature.**

TABLE 2. **Performance from different sets of syntactic features.**

Type	Precision	Recall	F score	Type	Precision	Recall	F score
BOW	0.8824	0.8559	0.8689	TFIDF	0.8931	0.8553	0.8737
BOW + F G 1,2,3	**0.8952**	0.8768	0.8859	TFIDF+FG1,2,3	**0.8955**	0.8763	0.8858
BOW + F G 1	**0.8925**	**0.8821**	**0.8872**	TFIDF + F G 1	**0.8975**	**0.8854**	**0.8914**
BOW + F G 2	0.8752	0.8631	0.8691	TFIDF + F G 2	0.8802	0.8697	0.8749
BOW + F G 3	0.8705	0.8521	0.8612	TFIDF + F G 3	0.8795	0.8531	0.8661

phrases, aspectual markers have been proven to be effective features. The fact that these are effective features strongly suggest that the prediction is based on the different event structures for literal and metaphoric meanings of the same verb type. For instance, the literal 走 *zhou* 'walk' generally involves intransitive activity, such as in 他走了一公里 *ta zhou le yi gongli he-walk-one-kilometer-LE* 'he walked for a kilometer'. On the other hand, the metaphoric sense tends to involve a noun phrase as an object, as in 走壞運 *zhou huai yun* walk-luck 'being unlucky'. The literal sense of the verb 熬 ao ' to stew' as in 熬湯 *ao tang* 'stewing soup' specifies an object to be created by the event after the verb; while the metaphoric sense as in 熬夜 *ao ye* stew night 'stay up' specify a time duration instead of an object to be created. We predicted that the syntactic properties of the metaphoric sense should differ from those of the literal senses.

Figure 3, which have the horizontal axis for conditional probabilities in metaphoric sense and the vertical axis for the conditional probabilities in literal sense, shows that the three group of features have different effectiveness in performance. Each line in Figure 3 represents a sense distribution of a verb. The syntactic feature as measurements can be grouped to improve detection results. As shown in Figure 3, the transitivity feature from Group 1 can better distinguish the difference between each verb in terms of metaphoric and literal readings. The passive feature from Group 2 has less predictive power. Lastly, the disposal feature from Group 3 does not contribute much.

D. EXPERIMENT 2: GENERALIZATIONS BASED ON RADICAL GROUPS

Our first study relies crucially on the hypothesis that Chinese radical groups are natural classification of event types. However, to prove this hypothesis, we need to show that all verbs within the same radical group, not just the ones we studied, share similar event types. Hence, extending the experimental design of [42], we add an experiment of generalizations in order to test whether the syntactic features model works. New characters were added to eight radical groups, as summarized in Table 3.

The same set of constructions for each radical group is applied to the newly added verbs in a machine learning model.

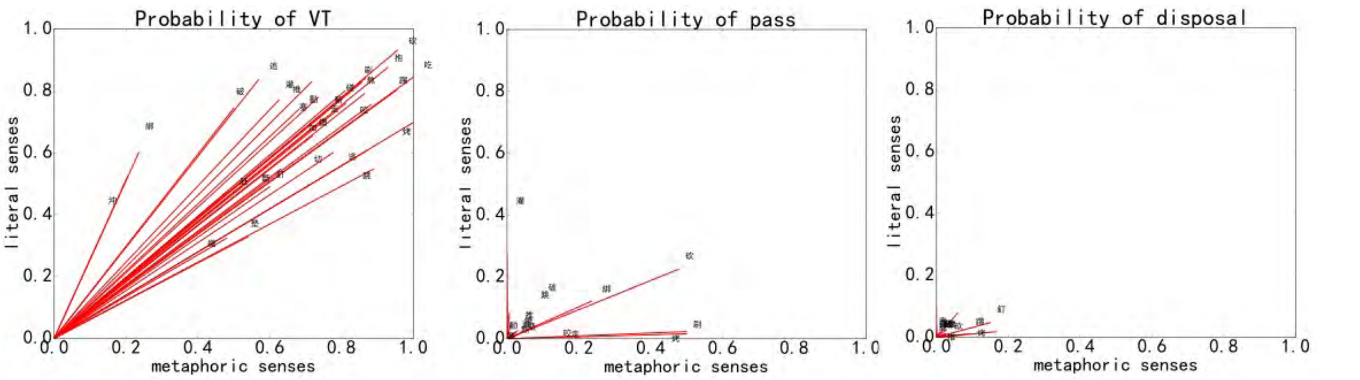

FIGURE 3. Distribution of literal and metaphoric senses based on one syntactic feature.

TABLE 3. Newly added characters for the radicals groups.

Radical	火huo 'fire'	水shui 'water'	土tu 'mud'	金 jin 'gold'	刀dao 'knife'	糸 mi 'thread'	口 kou 'mouth'	足 zu 'foot'
Characters in the test group	炸 *zha* 'fry' 炒 *chao* 'sauté'	泡 *pao* 'soak' 洗 *xi* 'wash'	壓 *ya* 'press' 埋 *mai* 'bury'	釣 *diao* 'fish'	刮 *gua* 'scrape' 割 *qe* 'cut'	綑 *kun* 'coil' 編 *bian* 'knit'	吞 *tun* ''swallow' 吸 *xi* 'suck'	跑 *pao* 'run' 踩 *cai* 'step'

TABLE 4. Performance from different sets of syntactic features.

Type	F-score	Precision	Recall	Type	F-score	Precision	Recall
Baseline(BOW)	0.7432	0.7442	0.7423	Baseline(TFIDF)	0.7573	0.7582	0.7576
Test group(BOW)	0.8332	0.7752	0.9008	Test group(TFIDF)	0.8455	0.7987	0.9554

Note that the adopted baseline is bag-of-words with Tf-idf. In the test group, we added the proposed syntactic features to the data containing new characters listed in Table 3. The results are summarized in Table 4, which shows that the incorporation of the syntactic features has improved the model in the F-score, precision and recall.

The improvement indicates that the proposed features can be effectively extended to other characters based on the trained radical groups. The effectiveness shows that the characters within the radical groups have similar eventive information. According to this generalization task, the classification of radical groups is helpful in executing metaphor detection by other characters in the group instead of by single lexemes.

VI. METAPHOR AS CULTURALLY GROUNDED PACKAGING OF COMPLEX EVENTS

Our Phrase 1 experiments show that literal and metaphoric senses of the same verb form have different event structures. Given that literal senses of a verb tend to occur in a set of syntactic constructions, we can detect non-literal senses, including metaphoric usages, of the verb form when it does not appear in that set of constructions. This is why the proposed syntactic constructions are effective features for the machine learning model for metaphor detection. The results also show that literal and metaphoric senses are meaning-form pairs. Each of the two groups of senses has a tendency to occur in a specific set of environments. Our phase 2 experiment show that the proposed syntactic features not only work in the trained group of verbs but also work in the test group. Notably, verbs that share the same radical tend to have similar event structures, which can be observed in their syntactic distribution.

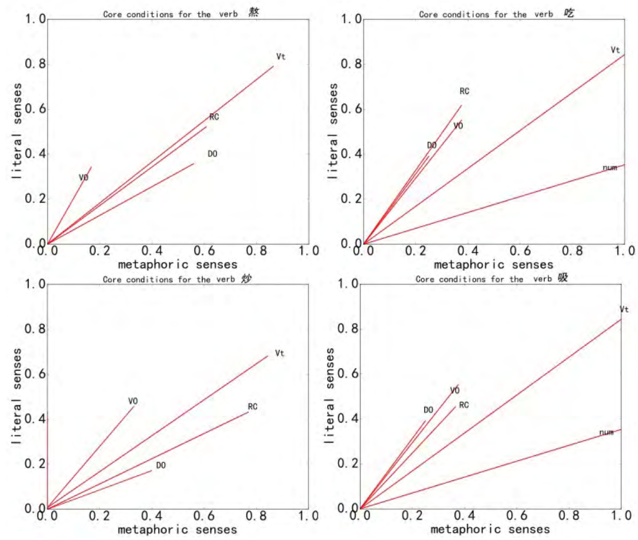

FIGURE 4. Examples of how metaphoric and literal senses defined by a set of syntactic features.

Figure 4 has verbs from the fire radical, 熬 *ao* 'simmer' and 炒 *chao* 'stir fry', and the verbs from the mouth radical, 吃 *chi* 'eat' and 吸 *xi* 'suck'. 熬 *ao* 'simmer' and 吃 *chi* 'eat' are included in Experiment 1, while 炒 *chao* 'stir fry' and 吸 *xi* 'suck' are from Experiment 2. It is important to note that each verb has a different set of most effective features. The comparison between two experiments shows that the distribution of literal and metaphoric senses of verbs with the same radical can be characterized by the same core set of syntactic features. A feature with a stronger predictive power has a bigger difference in the probability between the literal and metaphoric senses, as shown in Figure 4. The feature of numeral phrases is effective for the verbs with the mouth radical, but less so for the verbs with the fire radical. In other words, the metaphor senses of each verb form can be identified by a few most relevant syntactic features. The features do not only work for individual verbs, but also work for verbs grouped by radicals.

We further examine the effectiveness of the proposed syntactic features. As discussed earlier, the syntactic features transitivity (Vt), numeral phrases (Num), relative clauses (RC), compounding (VV), word order (VO), and double- object construction (DO), are most effective ones. In other words, these mark the constructions that play crucial roles in differentiating literal and non-literal senses. First, a verb sense tends to be literal when a numeral phrase is involved because only concrete objects can be enumerated. Second, metaphoric senses tend to occur when there is a presence of a relative clause, which serves the purpose of modification. This is because metaphoric sense, compared with literal sense, more likely requires elaboration. Third, due to the differences of event types, the transitivity of a verb is likely to change, hence the transitivity feature is effective.

Regarding compounding in morphology, the occurrence of another verb provides additional information and thus the new event structure will be different from the original one. Similarly, when a verb adds an additional object to appear in the double-object construction, it is a strong sign of changed event types. Word order as the main device for information structure is another crucial feature in the model. Since each of the syntactic features links to a particular aspect of a conceptual event, its change is an informative indicator of which sense, literal or metaphoric, is in use. Somewhat surprisingly, the features in Group 3 do not contribute much to whole model. The information they provide is less crucial in detecting changes of event types. Our result is consistent with Levin's study of English verb classes [54], which show that argument changing diathesis can be the cornerstone of English verb classes.

Chinese radicals are organized based on the ontological structure, which refers to the organization of knowledge structure and the representation of knowledge system in terms of relations between concepts [53]. Thus radicals can be grouped to form a higher-level category in the ontological structure. For example, the radicals discussed in this study can be classified into four larger semantic categories, which are instruments, body parts, materials, movements, as shown in Table 5.

Based on Hantology [5], [51], the four radical-encoded concepts shared by the group of characters in Table 5 can be mapped directly to IEEE SUMO [2]. The mapping result,

TABLE 5. Higher ontological level categories of radicals.

Physical	Object	Body parts	扌*shou* 'hand', 口*kou* 'mouth'
		Materials	火*huo*'fire', 水*shui*'water', 土*tu*'mud'
		Movements	辶*chuo* 'interittent', 足*zu* 'foot', 走*zou* 'walk', 力*li* 'power'
	Process	Instruments	石*shi* 'stone', 刀*dao* 'knife', 金*jin* 'gold', 斤*jin* 'ax', 糸*mi* 'thread'

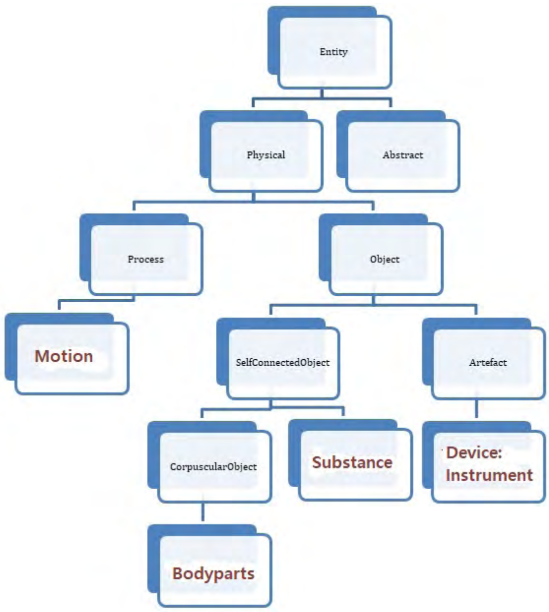

FIGURE 5. Trimmed upper ontology including the four radical encoded concept atoms (based on IEEE SUMO, with non-relevant brancheds ignored).

showed as trimmed tree without the non-relevant branches, in presented as Figure 5. It can be seen that all radical represented concepts are fairly close to the top of upper ontology, 3-5 levels removed from the root node. This is consistent with the view that the Chinese radical orthography is a culturally grounded linguistic ontology [16]. With this mapping to ontology, the result of our current study can be adopted for knowledge system and knowledge engineering studies such as construction of language and/or culture specific ontologies, representation and computation of metaphoric meanings, or cross-lingual, cross-cultural, or cross-domain knowledge transfer or integration.

The differences in terms of the distribution of the literal and metaphoric senses of the four semantic groups can be nicely captured as different vectors, as shown in Figure 6, which includes the verbs from both Experiment 1 and Experiment 2. Each group stands for a broader conceptual class, including body parts, materials, movements and instrument. Each has a different set of effective features in detecting metaphors.

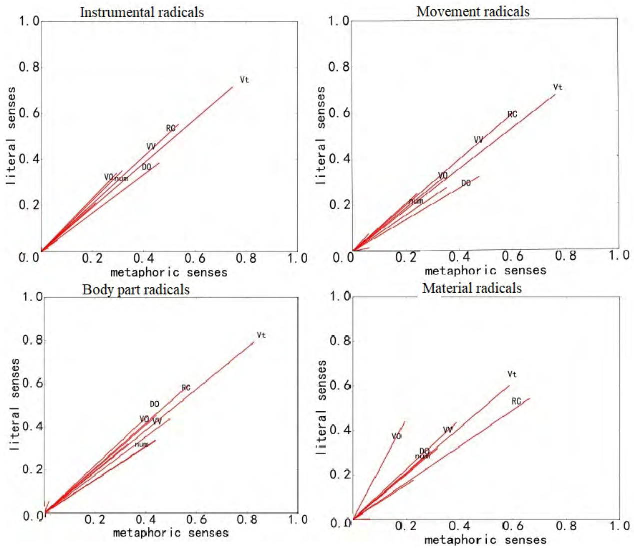

FIGURE 6. Examples of the effective syntactic features for a higher-level semantic category.

As shown in Figure 6, each conceptual class has a different arrangement of the features.

Similarly, the literal sense of a larger semantic group can be identified by its syntactic distribution. When a sense of a verb in a larger semantic group does not occur in the set of syntactic features where the literal senses generally occur, it is likely to be metaphoric. Our design shows that syntactic features can offer informative clues in detecting metaphoric senses.

VII. CONCLUSION

Computational approach on figurative language and linguistic creativity has been recognized as future direction of AI [54]. Figurative language is pervasive in our daily life and often provides the most crucial piece of tightly packed information. Due to its versatility, creativity, and deviation from literal meaning, figurative language poses great challenges and attracts considerable attention in NLP [17], [54]. This study aims to go beyond simple metaphor detection by capturing linguistic creativity in the cultural context. The cultural context is represented by ontology, following the earlier proposal of metaphor proposing in [1] and [55]. We elaborated this approach of detecting metaphoric senses by the innovation of including eventive information encoded in radicals. The advantage of including radicals is the automatic introduction of culturally grounded conceptual groups. These culturally grounded conceptual groups in turn correspond to broad event types and allow us to make use of their shared distributional syntactic structure through the state-of- the-art tool of word embedding. Thus, literal and metaphoric meanings can be differentiated by their syntactic distributions. This study provides a new method to define where literal senses tend to occur. This way we can effectively capture all possible metaphoric senses, including the conventional ones and creative ones. A verb used in a creative way can also be detected since it deviates from the literal senses. The natural language processing task can thus produce and detect variations and creative expressions. The concept is in line with [17] in that computational processing can be effectively used to capture the linguistic creativity. Note that by taking the sub-lexical orthographic features of Chinese, our approach complements all standard word-embedding studies that typically focus on contexts. Hence our study can be synergized with other word-embedding based approaches and find new results.

It is important to note that our proposed approach can be applied beyond detection of non-literal meaning in Chinese. Most crucially, the use of syntactic features marking eventive information can be applied in all language, such as in previous studies using Levin's English verb classes [56] or Pustejovsky's generative lexicon and event annotation [3], [55]. Our study suggests that similar approaches, as well as other available eventive information resources such as WordNet, FrameNet, and Tongyici Cilin, could also be leveraged in the detecting of metaphors and other figurative meaning. The syntactic features proven to be relevant for detection of event types involved in metaphor detection, such as aspectual markers, word order, and argument structures, should also be applicable in other language and other similar tasks of processing of non-literal meanings. It is important to note that our current approach refocuses metaphor detection on the inherent eventive information of metaphoric usages of a verb instead of on its contextual information as discussed in previous literature. By focusing on the usage of a verb itself without relying on semantic classification of its context, our approach should be more robust in applicable tasks and in requiring fewer resources. Our algorithm of modeling eventive information can provide a pathway to incorporate analysis of event types in deep learning as future studies.

In sum, treating ontological information represented in the Chinese writing system as culturally bound eventive information facilitates processing of metaphor. The specific methodology introduced is applicable to all Sinitic languages as well as Sino-spheric languages sharing Chinese orthography as their cultural heritage, such as Japanese and Korean. As shown in [16], lexical processing in Japanese and other languages based on Chinese orthography can be automatically bootstrapped. Eventive information in many languages can be automatically or semi-automatically extracted through the OntoLex interface approach [57]. A recent study [57] also provided evidence to support the reality of these ontological classifications, especially that qualia are psychologically real, further strengthening the theoretical basis of our current work. Results of the study suggest the potential applications for the use of eventive information to semantic processing in a wide range of current AI applications as well as in the potential benefit of leveraging culturally grounded linguistic features in a wide range of NLP tasks.

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