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Computational Mechanisms for Metaphor in Languages: A Survey

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Abstract Metaphor computation has attracted more and more attention because metaphor, to some extent, is the focus of mind and language mechanism. However, it encounters problems not only due to the rich expressive power of natural language but also due to cognitive nature of human being. Therefore machine-understanding of metaphor is now becoming a bottle-neck in natural language processing and machine translation. This paper first suggests how a metaphor is understood and then presents a survey of current computational approaches, in terms of their linguistic historical roots, underlying foundations, methods and techniques currently used, advantages, limitations, and future trends. A comparison between metaphors in English and Chinese languages is also introduced because compared with development in English language Chinese metaphor computation is just at its starting stage. So a separate summarization of current progress made in Chinese metaphor computation is presented. As a conclusion, a few suggestions are proposed for further research on metaphor computation especially on Chinese metaphor computation.

Keywords metaphor understanding, natural language processing, Chinese language, computational model, logic

1 Introduction

Metaphorical property of natural language becomes more and more attractive. Researchers have realized that metaphor known as an anomalous use but pervasive linguistic phenomenon is the focus of mind and language mechanism. Within the last few decades, a great deal of attention has been paid to computational view of metaphor understanding. According to computational linguistics and natural language processing, metaphor computation will play an active role in discourse understanding and machine translation[1]. However, to date, there has been no robust, broadly applicable computational metaphor interpretation system.

Metaphor research may trace back to Aristotle era whose Comparison and Substitution view regarded metaphor as a rhetorical expression which functions like a kind of accessional, dispensable "decorations". The fact is that he failed to find out and reveal the essence of metaphor. Since 1930s, Richard and Black had proposed Interaction View from the aspects of rhetoric philosophy and structuralism respectively[2]. They promoted metaphor analysis to sentence level and pointed out that the process of understanding a metaphor should involve interaction of concepts in source and target domains. Interaction View then led to metaphor analysis from the perspective of cognition. In 1980s, Lakoff and Johnson proposed Conceptual View and argued that rather than being a rare form of creative language, some metaphors are ubiquitous, highly structured, and relevant to cognition[3]. Later on, more cognitive models such as Structure-Mapping[4,5], Contemporary Theory[6] and Structural mapping model emerged[7,8]. Moreover metaphor research also attracted the attention of pragmatists. Searle[9] concluded eight principles for English metaphor recognition and understanding in his Speech Act Theory.

By contrast with research on metaphors in English language, Chinese linguists limited their enthusiasm to rhetoric and psychological feature of metaphor[2,10−17]. Research on Chinese metaphor from computational view is still at a very early stage[1,18−25].

This paper concentrates on computational view of metaphor. An integrated analysis of metaphor understanding process is first presented. Then representative computational models of English metaphors are reviewed: including advantages and limitations of rule-based approaches and statistic-based approaches appeared since 1970s. Then a brief comparison between English and Chinese metaphors is discussed and current achievements on Chinese metaphor computation are also presented. In the end of this paper a few suggestions are proposed to enrich further computational research on metaphors especially on Chinese metaphors.

2 Metaphor Understanding Process

Before we go into detail we give a brief description of how a metaphor is understood. Unfortunately, up till now, no demonstrations in neural science showed how people understand a language. As a result it is necessary to find out a rational and explicit description on how people understand a metaphor. Then machine-understanding of metaphor could be designed following the process.

There are many different discussions on the process of understanding a metaphor[9]. We draw a conclusion and

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propose the process how people understand a metaphor proceeds in three stages:

The first stage is to recognize a metaphor. In this stage, people point out the metaphor and mark up the metaphoric components. Consider the example as follows.

Example 1. An atom is a solar system[31]. When people recognize the metaphor they will also recognize *atom* is the topic and *solar system* is the vehicle.

The second stage is to analyze it. In this stage, people analyze components of the metaphor they have found and try to set up an associated mapping between topic and vehicle in order to pick out some similarities or grounds between the two concepts.

The third and last stage is to interpret it. In this stage the result or the output of the second stage will be interpreted by usual expressions, and the true meaning will be generated. For metaphor of Example 1 the interpretation would be "nucleus are in the center of an atom, and electrons surround nucleus on their orbits" and the like.

According to human beings the first stage seems to occur so instantaneously that it is usually ignored. And the analysis and interpretation stages also appear unconspicuous because most of the time when people understand a metaphor they do not speak out the specific interpretation of it. They just keep the meaning in mind and act as "I know what you mean". However, if we want a computer to understand a metaphor we intensively expect the machine "speak out" the real meaning rather than "just keeping it in mind." Metaphor computation is just the research to make a machine "find out" a metaphor and "speak out" its true meaning. As a result all the details of all the three stages need to be considered and resolved.

3 Computational Models for Metaphors in English Language

Most of the recent achievements in metaphor computation have focused on English language. Those methods provide the very good model to be promoted to other languages. The main approaches can be divided into two categories: rule-based approaches and statistic-based approaches.

3.1 Rule-Based Approaches

Approaches based on rules[26–28] are derived from classical theories of metaphor in linguistics[29] and psychology, including approaches based on metaphor semantics, knowledge representation, possible-world semantics and logic analysis.

3.1.1 Approaches Based on Metaphor Semantics

Metaphor-semantics-based approaches argue that to understand a metaphor should be different from to understand literal sentences. They do not emphasize the application of metaphorical knowledge. All the input sentences are regarded as statements unless there are contradictories in literal meaning obtaining.

3.1.1.1 Preference Semantics

Wilks[30] in his Preference Semantics Theory presents a method called anomalous breaking of selectional preference restrictions. He believes that the emergence of a metaphor will necessarily lead to a semantic preference breaking. Then a *metaphor recognition* module is designed to detect anomalies of semantic restrictions and is added to the preference semantics model to estimate whether an input sentence is a metaphor. As for a recognized metaphor it will be interpreted by an assistant interpretation mechanism with a scene knowledge structure described with pseudo-text. Once an anomaly of semantic restriction is triggered, the interpretation system will select a suitable semantic framework from the pseudo-text and then map the framework onto it. Pseudo-text is just like predicative entity knowledge, for example the entity *car* has attributes like *non-living object*, *consuming gasoline*, *being able to run*, *can carry goods*, *speed* and etc. See Example 2.

Example 2. My car drinks gasoline. The formula of semantic preference of *drink* is ((*ANI SUBJ) (((FLOW STUFF) OBJE) (MOVE CAUSE))), that is, the agent of the action *drink* should be a living object. But *car* is not a living thing hence an anomaly of semantic preference is triggered. Then the interpretation system selects a corresponding framework which is *use* from the pseudo-text for a substitution. So the interpretation comes to be "My car uses gasoline".

Wilk's system divides metaphor understanding into two stages: recognition and interpretation and uses pseudo-text to represent knowledge. The idea of semantic preference breaking is reasonable but the simple substitution way to interpret a metaphor is really weak. Only well-formed simple sentences like metaphor of Example 2 may receive satisfactory processing results. The main limitation is that this method has a deficiency on extensibility. There are various metaphorical phenomena besides simple verbal metaphors. Semantic restrictions and knowledge representation could not be that easy. Moreover, it is rather difficult to write out all selectional preference restriction rules for all the verbs. If a verb is polysemous then the system does not tell how to represent its multiple selectional preference restriction rules and how to choose a correct one.

3.1.1.2 Collative Semantics

Fass[31,32] introduces a Collative Semantics (CS) for natural language processing which extends many of the main ideas of Preference Semantics. He proposes a system called Met* and provides an approach for recognizing and interpreting selected examples of metonymy and metaphor as well as anomalies and literalness in a semantic network. CS, and hence the Met* system which is part of it, has been implemented in a program called meta5.

According to the method, the main difference between metonymy and metaphor is that a metonymy is viewed as consisting of one or more semantic relations like *container for contents* and *part for whole*, whereas a metaphor is viewed as containing a relevant analogy. In sentences of the form "X is a Y", Met* first checks whether X and Y satisfy selectional restriction. If there is a satisfied selectional restriction, then the sentence is considered to literal and the process comes to the end. If no selectional restriction is found, then there is a confliction in "X is a Y". Then Met* turns to call metonymy-searching process. If a suitable metonymy is found, a literal relation between X and Y will be given by metonymy interpretation module. If there is no suitable metonymy, then the metonymy-searching process gives rise to metaphor-searching process. If no metonymy or metaphor relation between X and Y is found then "X is a Y" is considered to be an incorrect statement.

In Met* system the meaning of a verb is represented by a semantic vector whose elements are selectional restriction types of the verb. For example, the selectional restriction vector of *drink* is (*animal*, *drink*, *liquid*). To interpret a verbal metaphor is to select a common antecedent between meaning vector and preference vector of the verb. For instance, semantic vector of metaphor in Example 2 is (*car*, *drink*, *gasoline*) which is mismatching with (*animal*, *drink*, *liquid*). Then Met* looks for a common ancestor (*thing*, *use*, *energy-source*) for both of the vectors. As a result the interpretation comes to "My car uses gasoline as an energy source".

Met* system to some extent is a promotion of Wilks' method. In Met* system interpretation of metaphor is considered to be obtained by using common knowledge of concepts rather than specific meaning. And it also requires a recognition process using selectional restrictions to find out whether the sentence is nonliterary.

The process of Met* is actually a cognitive process which requires context, world knowledge and analogy inference. So Met* somewhat conforms to the cognition linguistics viewpoint. However Preference Semantics is limited to its ontology and hand-coded selection restrictions.

3.1.2 Approaches Based on Knowledge Representation

3.1.2.1 Semantic Network Approach

Weiner[33] analyzes metaphor from the aspects of salience, asymmetry, incongruity, hyperbole, inexpressibility, prototypicality and probable value range. The notion of salience makes use of the apparent fact that metaphorical statements are asymmetric: in isolated sentences of the form "A is (like) B" predicates (rather than attributes) have higher salience in B and lower salience in A. The effect is that some predicates in A become highly salient. An additional requirement is there are highly salient predicates of B that cannot apply to A. So highlighting and suppression are two aspects of metaphorical mechanism. Suppressing differences and highlighting selective similarities conform to the principle that *similarities come from differences*[1]. The selective similarities of the vehicle B follow the tenor A's domain, while the differences between B and A are eliminated by representing the topic A. Prototypicality means the concept of vehicle B is usually a prototype in a certain domain. Consider the following example.

Example 3. Mary's cheeks are like apples. It would probably mean to most people that *Mary's cheeks are round and red.* A different interpretation would be obtained if the concept of *round and red apple* was replaced by a *withered and rotten one* or even, for that matter, by a green one. Thus in order to deal with metaphors, it is necessary to know, in addition to the nature of the prototype, a range of probable values for a given predicate. This range can help determine whether the statement is literally true or not. Take Example 4.

Example 4. John's hands are like ice. If a range of possible temperatures were built into the representation for human hands, it would be known that *John's hands* could not possibly be literally as cold as *ice* (there could not be an actual equivalence of temperature in *hands* and in *ice*).

Weiner states that the process of metaphor understanding includes some sort of conceptual representation. He uses knowledge representation language KL-ONE to represent concepts and their relations in a generality hierarchy. Concepts are represented as structured objects. Specific concepts are enabled to inherit predicates from its antecedent concepts. It is convenient to represent predicate-relations and generic relations between concepts by KL-ONE. But there are still some limitations when processing prototypicality because metaphors are closely related to people's general awareness of things. To solve this problem Weiner introduces a sub-knowledge network to represent states of knowledge of the understanding agent, or the general cognition of the objects.

Weiner's semantic network approach emphasizes the importance of prototypes and takes into account the subjective factor that the agent who understands the metaphor. However metaphors with complex structure are not mentioned. The implementation is limited to hand-coded knowledge base of prototypes. But this limitation can be avoided along with the large-scale ontology such as SUMO, WordNet and so on.

3.1.2.2 Approaches Based on Instances

Martin[34−37] develops a Metaphor Interpretation, Denotation, and Acquisition System (MIDAS), a computational model of metaphor interpretation which has been integrated with the Unix Consultant (UC), a program that answers English questions about using Unix.

MIDAS uses KODIAK which is seen as an extended semantic network language in the tradition of KL-ONE to represent knowledge. KODIAK connects knowledge element through inherited mechanism and concept hierarchy structure.

In MIDAS conventional metaphors are explicitly represented as coherent sets of associations between source and target concepts. The underlying generic metaphor is referred to as a *core metaphor*. Correspondingly a metaphor that includes all the associations of a core metaphor and adds new associations that coherently extend the core metaphor is called *extended metaphor*. Therefore, the MIDAS consists of two sub-systems: Metaphor Interpretation System (MIS) and Metaphor Extended System. The MIS processes sentences in two steps:

In the first step, a syntactic parse and a preliminary semantic representation known as a primal representation are produced.

In the second step, this preliminary representation is replaced by the most specific set of concepts that can coherently explain the input. The specific set of concepts may be literal meaning of the input sentence or interpretation of a certain conventional metaphor. Two basic inference processes are used in the second step: one is called *concretion* which replaces an abstract concept by a specific one. The other is called *substitution* which substitutes a given source concept in a metaphor with the corresponding target concept.

A Metaphor Extension System (MES) will be invoked when, during the analysis of an input sentence, MIDAS find no coherent conventional reading. The MES refers to three extension inferences: *similarity-extension, core-extension* and the *combination* of the former two inferences. *Similarity-extension* inference follows analogy principle that features of concepts in source domain can be applied to describe analogous concepts in target domain. *Core-extension* inference relies on the presupposition that core-associations of concepts in source domain can be transferred to target domain. In extension algorithm any known metaphors that are potentially related to the new use are first searched, then the set of candidate metaphors are evaluated and the closest one to the current example is chosen to interpret it. After the interpretation the new interpreted metaphor is stored in the corpus.

Unix Consultant (UC) tries to find a literal answer to each question with which it is presented. If violations of literal selectional preference make this impossible, UC calls on MIDAS to search its hierarchical library of conventional metaphors for the one that explains the anomaly. If no such metaphor is found, MIDAS tries to generalize a known conventional metaphor by abstracting its components to the most-specific senses that encompass the question's anomalous language. MIDAS then records the most concrete metaphor descended from the new, general metaphor that provides an explanation for the query's language. MIDAS is driven by the idea that novel metaphors are derived from known, existing ones. The hierarchical structure of conventional metaphor is a regularity not captured by other computational approaches. Although MIDAS can quickly understand novel metaphors that are the descendants of metaphors in its memory, it cannot interpret compound metaphors or detect inter metaphorical relations besides inheritance.

Martin argues the most difference between MIDAS and other computational models is that MIDAS' knowledge-based approach can learn new metaphors automatically. But his so-called "knowledge" is just the relevant metaphors absorbed by the system. So it may be more appropriate to call MIDAS example-based approach.

3.1.2.3 Connectionist

Veale[38] proposes an up-down and bottom-up metaphor interpretation framework. The up-down part is called Conceptual Scaffolding which acquires associations and constructs semantic relations between concepts. The bottom-up part is called Sapper. Sapper represents a semantic model by means of a connectional structure in which the nodes denote concepts and the arcs denote relations of concepts. Metaphor is considered to be a means of learning new conceptual structure by linking existing diverse schemata in novel ways. This linkage of domains is achieved by augmenting the network with *conceptual bridges* which actually are activation-carrying connections that represent semantic similarity relations and link the tenor and vehicle schemata of the metaphor. When first created, a conceptual bridge is dormant and called *dormant bridge*. Constructing dormant bridges is to call a symbolic processing mode using *Triangulation rule* and *Squaring rule*. In *Triangulation Rule*, whenever two concepts share an association with a third concept (the associations may be of different strengths), this association provides evidence for a plausible (i.e., dormant) bridge between both schemata. For example, a conceptual bridge between the concepts *scalpel* and *cleaver* based upon the fact that both are readily associated with *blood* and *sharpness*. This bridge may then be awakened later when employed as part of a larger metaphor (see Example 5).

Example 5. Surgeons are Butchers. Squaring rule is considered to be second-order as it employs links rather than nodes as the evidential basis for performing structural inference. Such second-order strategies thus support an interplay between symbolic and connectionist components of the hybrid model. Because when dormant links are awakened they may instigate further high-level inference. For example, a dormant bridge is inferred with the schema of *General* and *Brain-Surgeon* on the basis of a burnt-in bridge between *Command-Centre* and *Brain*, which in turn was inferred using the triangulation rule.

CS/Sapper framework is based on Black's interaction view of metaphor. The dormant bridge awakened by CS/Sapper strengthens the weight of common properties of concepts in source and target domains. The framework of CS/Sapper well explains the cognitive nature of metaphor. However the semantic structures in CS/Sapper framework are still manual. Moreover the language of Sapper is too simple, in fact, we need more tags.

To avoid the difficulties when constructing hand-coding semantic networks Sun[39] develops a connectionist model using micro-features. The system generates the knowledge related to the given word. Through some back propagations and iterations a micro-feature vector for every word is obtained. An implication node in neural network is a micro-feature which has no specific interpretation. The training is carried out on sets of nouns and related adjectives. In order to interpret metaphors like "X is a Y" (X and Y are nouns in the training set) the system searches out salient adjectives in vehicle conceptual domain that is irrelevant to tenor domain. As a result the significant features in vehicle conceptual domain are transferred to tenor domain. This kind of view is consistent with Weiner's method. The main advantage is that metaphorical knowledge is generated by machine learning rather than hand-making and avoids the limitations of hand-coding knowledge bases.

3.1.3 Approaches Based on Possible-World Semantics

Understanding of metaphor involves reasoning with world knowledge so analogy inference and logic inference are available.

3.1.3.1 Structural Theory of Metaphor (STM)

Steinhart[40] proposes a metaphor logic system combined with analogy. He extends possible-world semantics to handle metaphors and make great use of the notion of structure to set up a Structural Theory of Metaphor (STM): if STM is correct, then metaphors are cognitively meaningful and are nontrivially logically linked with truth. The dictionary is regarded as a network of concepts. Literal and metaphorical truth-conditions are both defined in an intentional predicate calculus called extended predicate calculus (the XPC). As Steinhart concerned, some sentences in natural languages like English have multiple meanings. For metaphorical sentences there are at least two meanings: the literal meaning and the metaphorical meaning. Each meaning is a function from (possible) worlds to truth-values.

Steinhart distinguishes surface structures and deep structures of a language. Surface structures are sentences in natural language and deep structures are sets of propositions in XPC. He translates English surface structures into expressions in XPC. XPC is extended by three ways:

One way is adding thematic roles such as *AGENT*, *PATIENT*, *OGJECT*, *SOURCE*, *RECIPIENT* and *INSTRUMENT*. For instance, while the ordinary translation of "John loves Mary" is [*loves*(*John*, *Mary*)], the translation into XPC is [*loves*(AGENT: *John*, PATIENT: *Mary*)].

The second way is adding events which make an occurrence as an individual.

The third way is subdividing the logic space from possible worlds into situations including individuals with certain properties and the relationships between them.

Accessibility in metaphorical logic is analogy consistent in possible-world semantics. Situation S is accessible to T if and only if S is analogous to T. Steinhart has also develops a theory used by STM of analogy and analogical inference which is originated from Structural Mapping Theory (SMT) which emphasizes the similarity of the source domain and the target domain. The analogy between S and T is a structure-preserving mapping function f which correlates elements in S with analogous elements in T. In the theory of analogical inference an analogy denotes the common structure which both domains (target T and source S) share. The analogy in the form "A is to B as C is to D" means that there is a relation R such that $R(A, B) \in T$ and $R(C, D) \in S$. Then the analogy is thus a triple (S, T, f). If $R(x, y) \in S$ then $R(f(x), f(y)) \in T$. Steinhart uses Analogical Constraint Mapping Engine (ACME) as mapping function to transfer knowledge from source domain to target domain to create a new proposition. Then truth value of the new proposition is computed according to metaphorical truth value assignment rule.

The implemented program of STM is called NETMET. In NETMET the structure of knowledge base is as Fig.1 shows. Metaphor "An atom is a solar system" requires 16 propositions to make up of the knowledge. In the knowledge base *contains*, *orbits*, *surrounds* are predications. Q1 denotes "a solar system is composed by the sun, the asteroid belt, the planet system". P5 denotes "the planet surrounds the sun on its orbit". Possible worlds are constructed according to the specific knowledge base. Relations between the tenor and the vehicle are formed by analogous mapping.

Description of the Target Atom
P1: contains (atom, {nucleus, electroncloud})
P2: contains (electroncloud, {electronshell})
P3: contains (electronshell, {electron})
P4: orbits (AGENT: electron, PATIENT: nucleus)
P5: surrounds (AGENT: electroncloud, PATIENT: nucleus)

Description of the Source Solar System
Q1: contains (solarsystem, {sun, asteroidbelt, planetsys})
Q2: contains (asteroidbelt, {asteroid})
Q3: contains (planetsys, {planet, moon, ring})
Q4: contains (ring, {subring})
Q5: contains (subring, {debris})
Q6: orbits (AGENT: asteroid, PATIENT: sun)
Q7: orbits (AGENT: planetsys, PATIENT: sun)
Q8: orbits (AGENT: moon, PATIENT: planet)
Q9: orbits (AGENTA: debris, PATIENT: planet)
Q10: surrounds (AGENT: asteroidbelt, PATIENT: sun)

Fig.1. Knowledge structure for "an atom is a solar system" (see [40] Steinhart 2001, p.80).

In NETMET, knowledge bases for each metaphor are made by hand.

STM handles metaphors by extending possible-world semantics[41]. It uses truth-conditions and intensional predicate calculus (extended predicate calculus, XPC). STM is an auto-inference method which distinguishes literal and metaphorical meanings. However, STM is limited to systematic similarity between topic and vehicle. It may work well on structured metaphors like metaphor of Example 1. But it is helpless when it encounters more generic metaphors especially literary metaphors which involve subjective knowledge and selective inference.

3.1.4 Adaptive Logic

Based on Black's Interaction View D'Hanis[42] proposes an Adaptive Logic for metaphor analyzing (ALM). She argues that metaphor is a dynamic cognitive process. She also chose "X is Y" metaphors as objects. According to interaction view, X is the primary subject while Y is the secondary subject which will be used to explain certain properties of X. The main idea of ALM is as follows.

The first step is to find out all the properties of the secondary subject Y and put the properties into a set of logic presuppositions.

The second step is to project on or transfer the presupposition set to the primary subject X. The primary subject functions like a filter and selects the information consistent with the primary subject from the presupposition set.

ALM is non-monotonic and has a dynamic proof theory. In ALM a formal language L^* is constructed by adding literal predicate π and a metaphorical predicate π^*. This means that all predicates in this language are "doubled". The secondary subject is formalized by means of a metaphorical predicate, the primary one, as usual, by means of a literal predicate.

Example 6. The man is a wolf. It is formalized as $(\forall x)\ (Mx \supset W^*x)$.

ALM is characterized by three elements: an upper limited logic (ULL), a lower limited logic (LLL) and an adaptive strategy. The ULL incorporates the set of logical presuppositions of secondary subject. It assumes that everything we know about, for example *wolves* can be applied to *wolves**. LLL is a subset of ULL which drops some of these presuppositions. It presupposes that no information can be transferred to the primary subject. The idea behind an adaptive logic is that a set of premises is interpreted as much as possible in accordance with the presuppositions of ULL. The adaptive strategy tells how to interpret expressions as much as possible. In ALM strategy consists of inference rules.

The adaptive logic follows as much as possible the ULL, only when abnormalities are derived. It switches to LLL. Thus the adaptive logic oscillates between the two systems. See Example 7.

Example 7. John is a donkey. The associated properties with donkeys are:

Donkeys have long ears. (E)
Donkeys are stupid. (S)
Donkeys are stubborn. (T)
Donkeys bray. (B)

Then the premises could be

$$\{D^*j, (\forall x)(Dx \supset Ex), (\forall x)(Dx \supset Sx),$$
$$(\forall x)(Dx \supset Tx), (\forall x)(Dx \supset Bx)\}.$$

The associated properties with John are:

John is human. (H)

Then the premises could be

$$\{D^*j, (\forall x)(Dx \supset \sim Ex),$$
$$(\forall x)(Dx \supset \sim Bx)\}.$$

According to the premises of donkeys, the conclusions Ej, Sj, Tj, Bj are obtained. Then the premises of the primary subject *John* will filter the conclusions and got $\sim Ej$, $\sim Bj$. The final result of ALM analysis is $\sim(\forall x)(D^*x \supset Ex)$ and $\sim(\forall x)(D^*x \supset Bx)$. The conclusions rely on the information of the primary subject *John*. If more premises of John are added, the conclusions may be changed.

The adaptive logic of metaphor can capture the dynamics and unfixed features of concepts in a metaphor. However, ALM system just deals with analysis stage of metaphors and it cannot solve recognition or interpretation of metaphors. ALM is also limited to "X is Y" form and pre-established or recognized as metaphorical propositions and their primary and secondary subjects.

3.1.5 Metaphor Inference System

Barnden[43] develops a context-based reasoning system called ATT-Meta which can perform both belief reasoning and metaphor-based reasoning. ATT-Meta is a rule-based and goal-driven reasoning system. It focuses on metaphorical utterances about an agent's metal states and processes. A metaphorical utterance is considered to be the one that manifests a metaphorical view, where a metaphorical view is a conceptual view of one topic or domain as another.

Example 8. Mind as physical space. This is a metaphorical view stored in a pre-established knowledge set. Then "the two ideas were in different store-rooms in John's mind" is a natural-language manifestation of this view. The connotation is derived by:

Step 1. The literal meaning of the utterance is made at first. So we get "John's mind literally has physical store-rooms as parts" and "the ideas are in those store-rooms";

Step 2. Search for general knowledge about real physical store-rooms and other physical objects, locations or interactions in knowledge bases.

Step 3. Conversion rules function as a type of context bridging rule and maps information between the source and the target domain of a metaphorical view.

Contexts are used to handle conflicts and uncertainties in metaphor.

The ATT-Meta system incorporates belief reasoning, metaphor-based reasoning and uncertainty-handling in a unified framework. But it lacks a proper treatment of more generic metaphors except for mind-state metaphors.

3.2 Approaches Based on Statistics

Along with developments in corpus linguistics it becomes more common to process language by statistic-based techniques[44−48]. Besides Kintsch makes use of Latent Semantic Analysis to extract semantic information mining from corpus, Mason also presents a corpus-based metaphor extracting engine called CorMet.

3.2.1 Vector Space Model

Kintsch[45,46] develops a computational system (CI-LSA framework) of "X *is* Y" metaphor comprehension using semantic vector space. The system first makes use of Latent Semantic Analysis (LSA) and tries to get a bag-of-words which have relevant or similar meaning to X and Y by computing semantic distances. And then a Construction-Integration (CI) model is added to select words which have close semantic distance with the vehicle Y from the bag-of-words. The selected words are then used to make up of a feedback network with the tenor (topic) X. In the feedback network semantic association of each word with X will be computed by parameters of context. As a result words that have high semantic association with X will be picked out to represent the meaning of metaphor "X is Y". The example of vector space matrix of metaphor is as follows.

Example 9. "My lawyer is a shark" is generated from a corpus of some 37,000 documents containing over 92,000 different word types — a total of about 11 million word tokens. Then singular value decomposition (SVD) is applied to the matrix to compute semantic distances among items. As a result the word *shark* is relevant to *dolphin*, *fish*, *driver* and *viciousness*, whereas *lawyer* is relevant to *justice, crime, viciousness.* Although we cannot find out direct relation between *lawyer* and *shark*, when *shark* is added to the vector space of *lawyer* we find that the similarity of lawyer and viciousness is increased, that is, *viciousness* is enhanced in the meaning of metaphor in Example 9. Then the metaphor can be interpreted as "my lawyer is vicious".

The rationale of Kintsch's method is Interaction Theory which states that the meaning of metaphor is affected by interaction of the topic and the vehicle. Similar to Weiner's method, Kintsch's method just represents metaphor by transferring properties which are isolated items of individuals rather than relations of items. Therefore, Kintsch's method is in fact a corpus-based manifestation of salience theory of Weiner.

3.2.2 Corpus-Based CorMet

Mason[47,48] develops a corpus-based system CorMet to deal with conventional metaphor recognition and analysis problems. Former computational models with hand-coded knowledge bases are limited in categoricalness and versatility. To avoid this limitation CorMet extracts metaphorical mappings between concepts by finding systematic variations in domain-specific selectional preferences, which are inferred from large, dynamically mined Internet corpora.

The first step is searching the Net for Domain Corpora. The process is submitting queries, which consists of a domain keywords tabulate and OR and AND logic instruction operators, to the search engine to mine documents in certain domain. Then the mined documents are parsed with the apple pie parser. Case frames are extracted from parsed sentences using templates; for instance, (S (NP & OBJ) (VP (were j was j got j get) (VP WORDFORM-PASSIVE)) is used to extract roles for passive sentences.

The second step is finding Characteristic Predicates. Learning the selectional preferences for a verb in a domain is expensive in terms of time, so CorMet finds a small set of important verbs in each domain. To find domain-characteristic verbs, CorMet finds the ratio of occurrences of each word stem to the total number of stems in the domain corpus. The frequency of each stem in the corpus is compared to its frequency in an English-language frequency dictionary. Verb stems with the highest relative frequency are considered characteristic. For example, in LAB domain the frequency of verb *vapor* is 0.0007 while in English-language frequency dictionary it is 5.2×10^{-7}. Then the relative frequency of *vapor* is 1,325.237 showing that the probability vapor appears in the LAB domain is by far higher than in the general domain. Twenty verb stems with the highest relative frequency are remained as characteristic predicates. For example characteristic predicates in LAB domain are: {*oxidize*, *sulfate*, *fluorine*, *vapor*, *titrate*, *adsorb*, *electroplate*, *valence*, *atomize*, *anneal*, *sinter*, *substitute*, *compound*, *hydrate*, *frit*, *ionize*, *deactivate*, *intermix*, *halogenate*, *solubilize*} and in FINANCE domain are: {*amortize*, *arbitrate*, *labor*, *overvalue*, *outsource*, *escrow*, *repurchase*, *refinance*, *forecast*, *invest*, *discount*, *stock*, *certify*, *bank*, *credit*, *yield*, *bond*, *rate*, *reinvest*, *leverage*}.

The third step is Selectional Preference Learning. CorMet uses selectional-preference-learning algorithm to get a verb semantic preference which is an overall measure of the choosiness of a case slot measured by selectional-preference strength, $SR(p)$. Case slots selected in CorMet are *subject*, *object*, *indirect object*, *to-object*, *from-object* and *with-object*. $SR(p)$ is defined as the relative entropy of posterior probability $P(c|p)$ and prior probability $P(c)$ (where $P(c)$ is the a priori probability of the appearance of a WordNet[49] node c, or one of its descendants, and $P(c|p)$ is the probability of that node or one of its descendants appearing in a case slot p). (See (1))

$$S_R(p) = D(P(c|p)\|P(c)) = \sum_c P(c|p)\log\frac{P(c|p)}{P(c)}, \tag{1}$$

$$\Lambda_R(p,c) = \frac{1}{S_R(p)}P(c|p)\log\frac{P(c|p)}{P(c)}. \tag{2}$$

The degree to which a case slot selects for a particular node is measured by selectional Association (see (2)). The selectional-preference predicate is presented in a quarter (*verb*, *case*, *node*, A) which represents that the selecional-preference for node in WordNet to appear in the verb case is A. Then a predicate's selectional preferences are represented as vectors whose n-th element represents the selectional association of the n-th WordNet node for that predicate. The nearest-neighbor clustering algorithm (KNN) is used to build clusters and to obtain various characteristic conceptual clusters and their predicate sets.

The fourth step is determining transfer direction of concept. CorMet uses polarity which is a measure of the directionality and magnitude of structure transfer between two concepts or two domains to determine the ingredient of two concepts in a metaphor. Nonzero polarity exists when language characteristic of a concept from one domain is used in a different domain of a different concept. If there is a predicate which is suitable to describe both concept a and concept b but there are also some predicates suitable for describing b but not suitable for a then a is the tenor concept and b is the vehicle concept. (See [48] for details of polarity computing algorithm.)

CorMet also provides a confidence measure for each metaphor it discovers. Confidence is judged by three things: number of predicates, polarity value and co-occurring mappings. The last one is mainly used to consider systematical property of the mapping.

CorMet system combines corpus analysis and semantic dictionary. The automatic acquisition of selectional-preference predicates by machine learning avoids the disadvantages of hand-coded knowledge bases. CorMet only works with conceptual metaphors in rather few domains. It only recognizes metaphors like Example 10.

Example 10. The company dissolved by judging that *dissolve* is a domain predicate in LAB while *company* is a keyword in FINANCE domain so the sentence is a metaphor.

Objectively speaking, Mason's idea highlights certain features of metaphor. However, it greatly relies on predicates in different domains. It requires metaphors being processed be highly structured and the predicates and concepts belong to a rather specific domain. In fact conditions CorMet demanded is too hash. So CorMet is only a test system and cannot be pervasive.

4 Current Achievements in Chinese Metaphor Computation

In former sections we mainly discussed the prominent achievements, evolutions and limitations of metaphor computation in English language. Because up till now, the worldwide research on machine-understanding of metaphor greatly limited to English language.

In this section we will concentrate our discussion on metaphors in Chinese language. Metaphor computation in Chinese language started late and is just at its starting stage.

Although the discussed methods or approaches in English language can be modified or applied to analyze Chinese metaphors, we still hope to establish a new system which is most suitable for Chinese metaphor processing. In languages with different nationalities metaphors may have great differences in sentence pattern and content understanding. Therefore, in this section we first give a brief analysis to the difference of metaphor understanding in the two languages and then review the research findings of our research on Chinese metaphor computation which could be the first computational view of metaphor in Chinese language. We also want our discussion to be an impetus to attract widespread attention on Chinese metaphor computation from the perspective of the nature of Chinese language.

4.1 Comparison: Chinese and English Metaphors

The cultural orientation appears extremely various in English and Chinese metaphor expressions. They have different cultural tradition, different living styles, manners and customs, aesthetic appeal, mentalities, faiths and natural environments which will lead to different cultural characteristics of metaphors.

1) Some metaphoric expressions in English language may never occur in Chinese expressions.

Example 11. "Mary *gave* John *a cold*" is considered to be a metaphor in English. The example involves the conventional metaphor that to *give* someone a *cold* means to *infect* them with a cold (Martin 1990, see [34]). While in Chinese, such an expression never appeals as a metaphor.

2) An identical metaphor may have rather different response in Chinese and in the Western nationalities[50].

Example 12. My love is like a dragon. A Chinese person will recognize the *love* to be *a man*, *a great man*, *a king style man*. The interpretation of the example to Chinese people will be "my boy-friend or my husband is as great as a dragon". While in the culture of western countries, the meaning of *dragon* is quite the reverse. In English the word *dragon* in metaphor of Example 12 mainly refers to *a woman*, *a virago*. In the Bible, *dragon* stands for *violent* and *brutal person*. So the interpretation of the example to a westerner may be "my girl-friend or my wife is as violent as a dragon".

Although there are commonplaces in English and Chinese metaphors, from the computational view of metaphor understanding it is necessary to give a separate consideration to Chinese metaphors.

4.2 Classification of Chinese Metaphors

The first work when we started to research on Chinese metaphors is to investigate various metaphor phenomena and to set up a classification system. Properties and logic representation of each category should be specified.

Yang *et al.*[18] have proposed a preliminary classification system of Chinese metaphors according to the cognitive structure of tenor, vehicle and their similarities. The classification system includes 9 categories (see Fig.2).

In Fig.2, the triangle is called Attribute Pyramid. Attributes on the top are the most distinctive while attributes at the bottom is less distinctive. Letter T denotes the topic or the tenor of a metaphor and V denotes the vehicle. S stands for similarity of T and V. The classification system is modified and testified within a 1,000-sentence Chinese metaphor corpus.

The merits of this classification work are that it first puts metaphor phenomena into several different categories from computational and cognitive angle and points out that metaphor computation should be pursued with different classifications.

However there are obvious limitations: the classification system only has 9 categories. That is inadequate. The classification work should be more elaborate. The structural feature of metaphor needs to be considered for it will be helpful at the recognition stage.

4.3 Recognition Strategy of Chinese Metaphors

Different kinds of metaphors need different processing strategies. So we hope that the result of recognition process tells us not only whether it is a metaphor but also which category it belongs to. Therefore we try to find out an effective algorithm in both classification and recognition.

Dai *et al.*[19,20] suggest a formulized Metaphorical Semantic Web (MSN) and primarily applies it to metaphor classification and recognition process.

In Dai's method a Chinese sentence is first formalized as a structure with three levels: object level, method level and attributes level. In metaphorical semantic network, a metaphor sentence is abstracted to a geometrical network in which the nodes denote metaphorical semantic characteristics and the directed arcs denote relationship of nodes. MSN tries to deduce metaphorical relationship by geometry inferential reasoning. There is a closed route called metaphorical route. Fig.3 is an MSN for Example 13.

Example 13. The ship ploughed the sea. In Fig.3 α is called *Invoking Arc* which denotes the literal semantic relationship between objects; β is called *World Knowledge Arc* which denotes general knowledge of the objects; θ is called *Metaphorical Arc* which means that there is a metaphorical relation (the two objects are different but have similarities) between two nodes (when the metaphorical relationship does not surely exist the θ is initialized by *Connatural Arc* γ); the node drawn in dashed denotes the implied tenor.

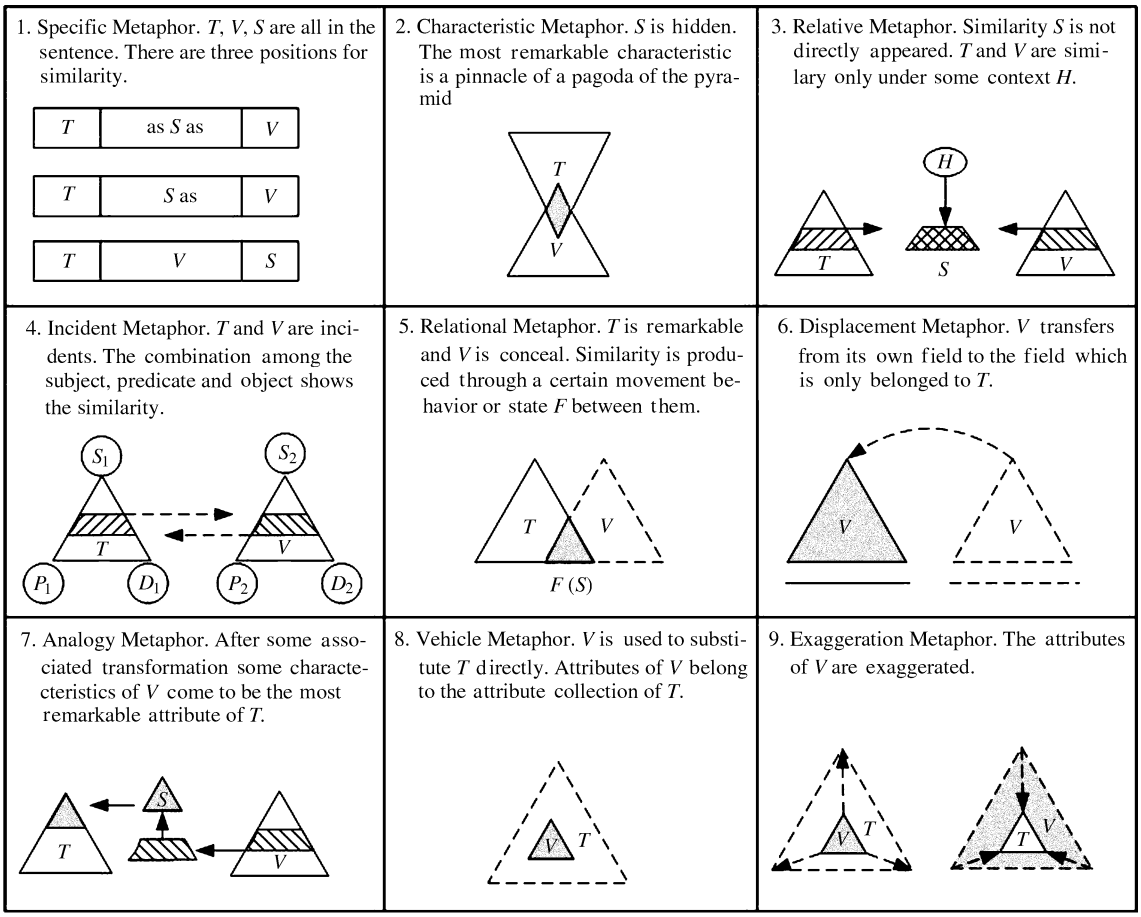

Fig.2. Classification system and its properties.

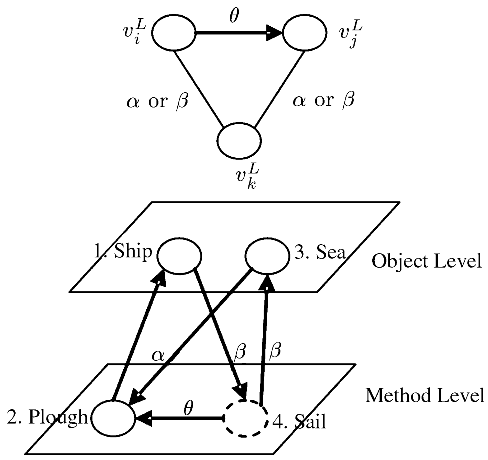

Fig.3. Example of metaphorical semantic network. (A closed route: $v_1^a\beta v_4^m\theta v_2^m\alpha v_1^0$ and $v_2^m\alpha v_3^o\beta v_4^m\theta v_2^m$.)

If there is no *Metaphorical Arc* θ the network is a common semantic network. When the metaphorical relation of two nodes is recognized (by computing the difference and similarity of the two objects) then the initial *Connatural Arc* γ is substituted by *Metaphorical Arc* θ. Different kinds of metaphors have different MSNs. The interpretation of metaphor is a process to change a common semantic network into a metaphorical semantic network.

MSN is different from conventional semantic network. It is constructed according to the structure and way of understanding metaphors. However the recognition stage is not so clear and the validity of this model need further experimental test.

4.4 Logic Systems of Chinese Metaphor

4.4.1 Zhang's Logic

Zhang *et al.*[21,22] propose a Chinese metaphor logic system from the aspect of solving logic omniscience and truth conditions of metaphors. Inspired by the local frame theory Zhang substitutes possible worlds with Pond Space, and introduces understanding operator U_p, a relational symbol $\prec$ and Gestalt rule. Pond space is just like a set of attributes or propositions of concepts. Formula $U_p a$ means an agent understands or accepts formula α. α is a proposition or a first-order predication in pond space p. Relational symbol $\prec$ is introduced to represent metaphor relation. Formula $\alpha \prec \beta$ is a Gestalt formula and denotes how analogous α is to β. Formula $U_p(\alpha \prec \beta)$ is true if in pond space p the agent understands that α is the same as β. Given some restrictions on variables, a metaphor analyzing system based on the logic system is established. The system has two levels: the upper control level is used to arrange the order and importance of each item in pond space; the lower semantics correlation level is constructed through statistic techniques. Pond spaces consist of sets of concepts (including entities and some relations) and are formed in semantics correlation level. If α is a noun, the system will get its associated concepts set by computing its corresponding semantic association with other concepts. Then relations and root metaphors of α will be merged into p on the control level. Only items (including α) that can make the tested proposition true in a propositional test can be reserved in p and those that make the tested proposition false will be deleted from p. The system identifies a metaphor through checking whether there is any gestalt formula. See Example 14.

Example 14. "A lawyer is a fox" can be formalized as:

$$U_{\{court,crime,case,sly\}}\ lawyer \wedge is \\ \wedge\ U_{\{forest,sly,doubtful,rabbit\}}\ fox.$$

This formula is then merged to $U_{\{sly\}}$ *Lawyer* $\prec$ *Fox* by Gestalt rule. $U_{\{sly\}}$ *Lawyer* $\prec$ *Fox* means if concerned with the attribute *sly* a *lawyer* is the same as a *fox*.

Zhang's metaphorical logic system provides a very good support for analysis of Chinese metaphors. However, it is insufficient to fill pond space only with various attributes. As we concerned, attribute is just one aspect of characteristics for a concept structure. The relations of concepts should also be considered. In addition, Gestalt rule may destroy the reliability of the logical system.

4.4.2 Huang's Logic

Huang *et al.*[23,24] propose a logical approach to metaphor analyzing. Differed from current metaphor understanding model, they introduce subjective factor in metaphor understanding, in their logic system, a modal operator U as understanding was added, which is a dual operator for knowing operator K in classical epistemic logic. They use mappings on conceptual spaces instead of accessibility relations to characterize the modal operator.

The system proposed is a T system. Huang also gives an analysis for Chinese metaphors in the form of "X is Y".

5 Conclusions and Prospects

We have discussed and reviewed computational models of metaphor from aspects of English and Chinese languages respectively.

In light of the current approaches, logic and knowledge representation based methods are on the dominant position. Logic based approaches trend to describe the intrinsic characteristics of metaphors while statistic based approaches trend to seek examples of metaphoric colligations of certain domains to interpret relatively fixed metaphors. These approaches show good performance within their well defined and a small group of metaphors. Therefore it is difficult to evaluate which method is preponderant.

However, all the methods have common limitations as follows.

1) They lack in-depth analysis of the phenomenon of metaphor so most of the methods only deal with the simplest and well formed metaphors like "X is Y" or "subject-verb-object". In fact there are various metaphors of complex sentence pattern and cognitive relations remained to be investigated.

2) Most of the methods do not clearly specify the process of how a metaphor is understood. We have recommended three stages when understanding a metaphor. However most of the methods have not found out that understanding process is a complex program and should be split into several smaller stages. Actually most approaches only deal with the analysis stage to already known metaphors. The recognition stage seems unclear and less effective. And the last interpretation stage is also inexplicit. It is a pity that recently there have been no convincing and pervasive recognition strategies and true meaning generation algorithms.

3) Just a few methods take into account the impact of people's subjective awareness (except Zhang's logic and Huang's logic). In fact the analysis and interpretation process of metaphor closely associate with people's subjective cognition.

There are lots of issues worth further investigation in metaphor computation field. Therefore these models or approaches show inadequate universality and cannot meet the requirement of broad applications.

As a conclusion we propose the following suggestions for further research on metaphor computation especially on Chinese metaphor interpretation.

1) Metaphor recognition should involve metaphor classification because different kinds of metaphors perform different cognitive properties and interpreting process. It is necessary to make good use of rhetoric achievements and the technique of statistics to set up a reasonable classification system based on machine understanding in order to make the recognition stage more specific and functional.

2) The cognitive nature of metaphor including comparison between concepts of topic and vehicle requires sufficient knowledge bases[49,51–53]. Models introduced in this paper more or less make use of knowledge base due to the representative and deductive property of those systems. An effective way is to combine rule-based and statistic-based approaches and use semantic dictionary and machine-learning technique to extract knowledge from large-scale corpus automatically.

3) Cognition and analogy representing and transferring of metaphor need further investigation. To accomplish this objective we can make use of epistemic logics to find out an analogical inference and provide an epistemic logical mechanism for metaphor paraphrasing[53]. Logic-based models for metaphor analyzing introduced in this paper indicate that it is feasible to represent logic of metaphor in possible-world semantics. Metaphorical meaning functions like the mapping from one conceptual domain to another. As a result how to find out suitable conceptual knowledge representing methods and inference mechanisms is the central problem at analysis and interpretation stages.

4) Metaphor computation may lead to an amelioration of machine translation and an intelligent upgrade of information retrieval (IR). To some extent metaphor computation deals with the essence of human language, so if metaphor processing module is added to Chinese-English machine translation to paraphrase stubborn sentences the quality of translation results may surely be improved. Moreover, if information retrieval merges metaphor processing, the results of IR will be to some extent enriched. For instance, web pages with the keywords like "terminate the process" will become the retrieval results of "how to kill the process".

As a result there is still a long way to go in metaphor computation research, especially in implementing functional and applicable computational systems. Solution of this problem in the future may bring to encouraging results to information processing.

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