A New Way to Conceptual Meaning Representation*

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Abstract

Conceptual meanings are the basis of concept-based semantic analyses, which play a key role in Natural Language Understanding. Traditionally, conceptual meanings were represented symbolically under the hypothesis of compositionality of conceptual features. This hypothesis is strongly supported by Feature List Theory in cognitive psychology, but Prototype Theory deny compositionality of concepts at all. However, there is now a consensus in the fields of linguistics and natural language processing that either the former or the later is not sufficient to characterize variety of concepts separately. In this paper, two steps are suggested to integrate compositionality and prototype of concepts, representations of conceptual meanings firstly described by multiple propositions are then converted to be represented subsymbolicly as vectors of real-valued units by using recursive auto-associative memory(RAAM) networks.

1 Introduction

Conceptual meanings are the basis of concept-based semantic analyses, which play a key role in natural language understanding.

Traditionally, conceptual meanings were represented symbolically under the hypothesis of compositionality of conceptual features. This hypothesis is strongly supported by Feature List Theory in cognitive psychology. In Feature List Theory, a concept is made up of two kinds of elements, one kind is defining features, which are common properties of a class of individuals, and another is relation between these defining features. Bourne, etc. (1971,1979) noted this kind of conceptual structure as following equation:

C=R(X,Y,...)

Where C is a concept, X, Y, ... are defining features existing commonly in a class of individuals which can be described by this concept; R is the rule used to integrate these features. Feature List Theory can be helpful in explaining some artificial conceptions, but unhopeful for some natural conceptions. Prototype Theory tries to describe a concept as a whole instead of by its sub-features in Feature List Theory. Rosch(1975) claimed that a concept is represented by its prototype, i.e., its central best example. There are also two factors in understanding a concept. One is prototype, another is named degree of category membership, which is the distance between an individual belongs to this conceptual category and the prototype, the individual can be characterized by this concept if its degree of category membership is within a permitted range. Prototype Theory has been used to interpret some natural concepts that Feature List Theory can not interpret. Prototype Theory deny the compositionality of meanings, it is also the standpoint of Langacker's gestalt meaning representation. Prototype Theory is capable in explaining some natural conceptions. However, there is now a consensus in the field of cognitive psychologist that either the Feature List Theory or Prototype Theory is not sufficient to characterize variety of concepts. Only by combining above two theories, can main problems in conceptual structures be solved (Gen, 1992).

In (Xiaojie, 1998), a feature prototype based conceptual structure was suggested by combining above two theories, it can be interpreted by following two formula:

$$P = F(p_1, p_2, \ldots, p_n) \qquad \text{(a)}$$

Where P is a conceptual prototype, $p_1, p_2, \ldots, p_n$ are n features, F is a rule or function that is used to synthesize these n features. When there are small perturbations on these conceptual features, i.e.:

$$P_\varepsilon = F(p_1 + \varepsilon_1, p_2 + \varepsilon_2, \ldots, p_n + \varepsilon_n) \qquad \text{(b)}$$

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When the perturbations $\varepsilon_1, \varepsilon_2, \ldots \varepsilon_n$ are within limits permitted , the new conception after perturbations which noted by P_ε should be similar to prototype P.

This paper tries to build a kind of meaning representation based on feature prototype based conceptual structures. We expect what we will build can be capable of both two sides: one is the realization of F that synthesizes multiple features, the other is to ensure the similarity between the old prototype and new conceptions after small perturbations, and this similarity can also be measured in a quantitative way.

The next section gives a two-step way to encode concepts, section 3 is a simple test, the final is conclusions.

2 Encoding of concepts

This section discusses a two-step way to form a features based prototype for a concept.

First, Features of concepts depict concepts from different views, each feature can be used in a kind of proposition to characterize a concept. For example, both 'yellow' and 'fruit' can be used to describe bananas, but they describe bananas in different way as that in following two propositions, one is:

Bananas are yellow.

Another is:

Bananas is a kind of fruit.

Note the predicates in above two propositions, 'yellow' and 'fruit' are both related to bananas, but in different ways, one is 'is', another is 'is a kind of', we use IS and IS-A-KIND-OF to stand for them separately. These are two different relations that features can be used to characterize a concept.

The way that features characterize concepts are various, but we think there are several basic modes among these variety of relations, currently, we suggest following eight basic relations between concepts and their features:

(1) (Concept) IS (Feature)
(2) (Concept) IS-A-KIND-OF (Feature)
(3) (Concept) FOR-EXAMPLE (Feature)
(4) (Concept) IS-A-PART-OF (Feature)
(5) (Concept) HAS-A-PART (Feature)
(6) (Concept) APPLY-TO (Feature)
(7) (Concept) ABLE (Feature)
(8) (Concept) ALLOW (Feature)

Above relations can be classified into two kinds: objective and subjective. The former include (1)—(6) and parts of (7), the later include (8) and parts of (7). There are very important differences between objective relations and subjective relations, features in the formers are generally objective existences, for example, concept "widower" can be characterized by three features belonging to this kind: "male", "adult" and "single", all of them are objective. While the subjective relations reflect certain social conceptions related to cultures. For example, bonzes can also be "male", "adult" and "single", but we generally don't think them widowers. The reason is bonzes are considered those who are not allowed to marry, noting that here are "not allowed"(limited by social cultures: single) but not "are not"(objective status: single), it is on this point that bonzes are distinguish from widowers.

It is also needed to point out that a feature of a concept may be itself a concept.

After characterizing a concept by several propositions separately, the second step to form a conceptual prototype is the synthesis of these propositions, that is:

$$\textbf{Concept} = \mathrm{I}\,(\,G_1(r_1,p_1),\; G_2(r_2,p_2),\; \ldots,\; G_n(r_n,p_n)\,) \tag{c}$$

Where $G_i(r_i,p_i)$, i=1,2,...n, are n propositions, r_i is the kind of relations, p_i is the corresponding feature, while I is a synthesis operator. Comparing to (a), then:

$$\mathrm{I}\,(\,G_1(r_1,p_1),\; G_2(r_2,p_2),\; \ldots,\; G_n(r_n,p_n)\,) = F(p_1,p_2,\ldots,p_n) \tag{d}$$

RAAM networks will be used as basic tools to implement the synthesis of multiple propositions. RAAM was firstly suggested by Pollack(1988) to show neural networks can also be used in encoding recursive data structures, such as tree. Figure 1 is a typical structure of RAAM networks.

As suggested above, each proposition used to depict a concept has three tuples, a concept , a feature and a relation. When the concept is fixed, only last two tuples are needed. So, in order to encode the concept depicted by several propositions, we need only construct a network like that in Figure 1. There are two areas in the input layer, one is for the code of a relation, another is for a feature, the output layer is as same as the input layer. The hidden layer has the same number of node as that in the feature area of input layer. The aim of network's learning is to encode the concept in hidden layer. For a fixed input sample (a pair of relation and feature (r_i,p_i)), a corresponding G_i is implemented by learning, and a code of concept is formed in hidden layer, after the training of all pair of input sample, operator I in (c) is implemented, this is also the complement of F in (a) and (d).

The algorithm of encoding of one concept is as follows:
1.chose all pair of features and relations used to define the concept, such as:

Concept r_1, p_1

Concept r_2, p_2

......

Concept r_n, p_n

Relations $r_1, r_2, \ldots r_n$ are encoded in n canonical codes (such as (1,0, ... ,0), (0,1,0, ... ,0), ...(0,0, ...,1)), codes of features $p_1, p_2, \ldots p_n$ are initiated with unknown mode (such as real-valued vector (0.5,0.5, ... ,0.5));
2.fetch a pair of above descriptions firstly, put codes of the relation and the feature into corresponding areas of input layer, BP algorithm is then executed, after finishing this sample, go to the next one till n;
3.repeat step 2 until error is small enough, codes in hidden layer are what is wanted for the concept.

For encoding of a group of concepts, iteration of above steps are needed, since some concepts may be features of another concepts, keep noting that those features must be substituted immediately by new codes after they have been changed during iterative process.

3 A simple test

Given six concepts: banana, apple, fruit, bird, penguin, and pigeon. For each concept, three features are enumerated accompanying three relations. For example, to the concept of 'apple', fruit, red, round are three features, their corresponding relations are IS-A-KIND-OF, IS and IS separately,

After the implement of above algorithm for a group of concepts, six real-valued vectors are got. By using clustering merge algorithm (Hartigan, 1975), similarities between these concepts are shown in Figure 2. The more similar, the more early they are merged.

4 Conclusions

This paper discusses a distributed representation of conceptual meanings, two steps are suggested, neural networks are used to encode conceptual features firstly described by propositions. Future works include to investigate another kinds of conceptual relations used to characterizing concepts, and test the capability and similarity of distributed representation for much more concepts.

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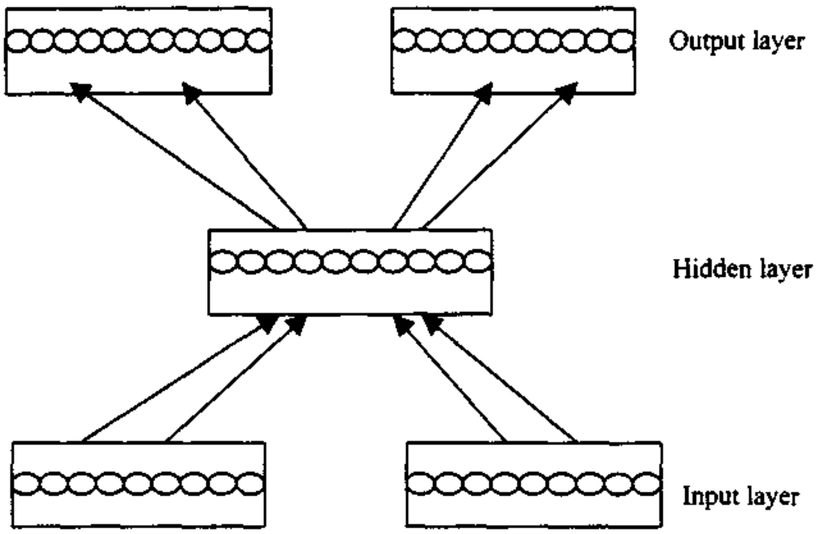

Figure 1

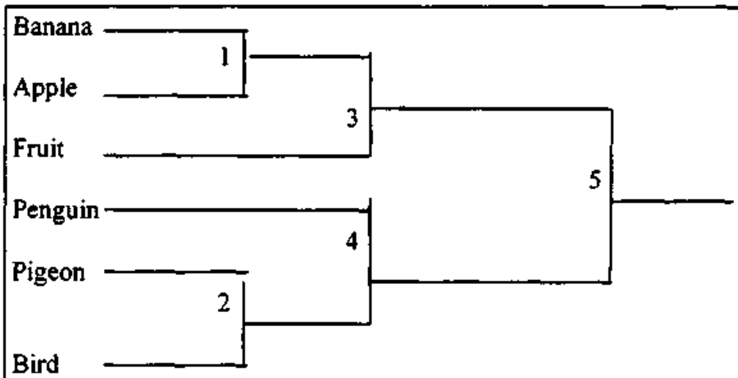

Figure 2