Pronoun Resolution with Markov Logic Networks

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Abstract. Pronoun resolution refers to the problem of determining the coreference linkages between the antecedents and the pronouns. We propose to employ a combined model of statistical learning and first-order logic, the Markov logic network (MLN). Our proposed model can more effectively characterize the pronoun coreference resolution process that requires conducting inference upon a variety of conditions. The influence of different types of constraints are also investigated.

1 Introduction

Understanding natural language has always been a challenging task. The variations in writing and the different means of conveying information pose huge difficulties in automatic understanding of text. To support language understanding tasks, different relations conveyed in text have to be identified and extracted. Among these relations, noun phrase coreference has been gaining increasing attention. Noun phrase coreference is the process of identifying the entities where different mentions belongs to. Coreference is a form of coherence in language representation. In representing ideas in language, a variety of forms is adopted in presenting the same idea. Different noun phrases may refer to the same entity. The resolving of the noun phrases is a crucial step for a broad range of language understanding processes such as relation extraction.

Human can understand noun phrase coreference via an inference process based on background knowledge of the noun phrases, agreement, such as gender and quantity, between phrases, the synonymity between phrases. Moreover, in maintaining the consistency of concepts, certain structures are usually being adopted for readers to follow the coherence within text.

Among the noun phrase coreference, pronoun resolution is a particularly important issue. A variety of pronouns may be used within a sentence, and may refer to different entities. In the following example, there exists three pronouns, namely, *who*, *his*, *it*. The pronouns *who* and *his* corefer with *John*, while *it* corefers with *the incident*.

John, *who* witnessed the incident, informed *his* friend about *it*.

Moreover, coreference between pronouns and entities are usually not restricted to the same sentence, exemplified as follows:

H. Li et al. (Eds.): AIRS 2008, LNCS 4993, pp. 153–164, 2008.

Mary met Susan yesterday. *She* was on *her* way home.

In this sentence, the pronoun *she* may refer to either *Mary* or *Susan*. Hence, the determination of which entity the pronoun corefers is an important issue.

Pronoun resolution is different from coreference resolution on proper nouns where surface features, such as string comparison, are not as significant. Despite the fact that pronouns are lack of rich semantic information, they are crucial in maintaining the coherence of knowledge representation in text. Hence, research from linguistic society has been keen on studying the characteristics of pronoun resolution, so as to discover the implicit relationship associated with the pronouns and their coreferred mentions. Based on those investigations, regularities of pronouns in language are studied and heuristic approaches are adopted in pronoun interpretation and on identifying pronoun coreferences.

However, there are no absolute rules on the way the pronouns corefer as there are infinite possibilities in language representation. Therefore, we propose to employ a combined model of statistical learning and first-order logic, the Markov logic network (MLN) [1]. Our proposed model can more effectively characterize the pronoun coreference resolution process that requires conducting inference upon a variety of conditions. The influence of different types of constraints are also investigated. With first-order logic, domain knowledge, such as, linguistic features or constraints as heuristic rules can be incorporated into coreference resolution, with the benefits of handling uncertainties.

We present how the problem of pronoun resolution can be formulated in MLN. An investigation on the adoption of pronoun resolution constraints will be presented. In next section, some related works regarding coreference resolution and pronoun resolution are included. In Section 3, background information on MLN will be introduced and a description on the formulation of pronoun resolution in MLN will be described in Section 4. Experiments and results will be presented in Section 5.

2 Related Work

For long, pronominal reference has been studied in the linguistic and cognitive society. A variety of views on the corresponding regularities are proposed [2]. Research on investigating the relations in pronominal reference, such as the clausal relationship and the structure, is still being studied [3].

While the works in the linguistic and cognitive society have been focused on the formal modeling of coreference relations, in the area of computational linguistic, research on performing automatic coreference resolution is being studied. The research in coreference resolution has been mainly focused on two directions, namely, linguistic and machines learning.

The linguistic approaches focus on adopting syntactic and semantic constraints on coreference resolution. The Hobb's algorithm [4] tackled pronoun resolution by searching through a syntactic parse tree of a sentence under some syntactic constraints. The centering theory [5] adopted the idea of coherence in texts and its idea is to trace the entities in focus.

In recent years, machine learning approaches are more widely adopted for coreference resolution, such as the Naive Bayes [6] and decision tree [7] approaches. Wellner and McCallum [8] tackled the coreference problems by using conditional models and graph partition approach. Besides pairwise resolution of mentions, coreference resolution is also considered as clustering mentions [9].

Moreover, much research has been carried on the investigation of features for the coreference resolution. A wide range of features has been experimented. Luo et al. [10] used syntactic features based on binding theory for improving pronoun resolution. Ng [11] investigated features with semantic knowledge. Ponzetto et al. [12] explored the use of semantic role labeling, and features with knowledge mined from WordNet and Wikipedia using a Maximum Entropy model.

Regarding pronoun resolution, both syntax-based and knowledge-based approaches are used. In particular, some works focused on resolving antecedents for third person pronouns. Lappin et al. [13] adopted a syntax-based approach which relies on syntactic information and determines the salience value of the candidate antecedents. In addition to syntactic information on texts, Bergsma et al. [14] proposed an approach based on syntactic paths, which analyze the dependency path information between potentially coreferent entities. Knowledge poor approaches with limited and shallow knowledge are also reported [15].

Moreover, world-knowledge is employed in retrieving the semantics-related information for pronoun resolution. Kehler et al. [16] investigated in the utility of corpus-based semantics for pronoun resolution and argued that the improvement is not significant. However, Yang et al. [17] investigated the use of semantic compatibility information obtained from web, and significantly improved the resolution of neutral pronouns, such as “it”.

3 Background

3.1 Pronoun Resolution

From the linguistic point of view, the distribution and location of different mentions within texts are governed by certain restrictions. In other words, through identifying whether mentions satisfy the constraints or not, the referential linkage can be deduced. Noun phrase coreference resolution involves resolving coreference relations mainly between proper noun phrases, nominal noun phrases, and pronouns. This paper focuses on the task of pronoun coreference.

Pronoun resolution is usually defined as identifying or matching the corresponding antecedent of the pronouns. Since pronouns are substituents for nouns, noun phrases or pronouns, which can help maintain the coherence of the representation of ideas in language or text, pronoun resolution is crucial to the understanding of language. However, pronoun resolution is not a trivial task. The pronoun itself contains little semantic information, which hinders the relation resolving between the pronouns and their antecedents. This poses differences between the pronoun resolution problem and the noun phrase coreference resolution problem, since matching features, such as phrase matches, commonly used in noun phrase coreference problem, are not applicable in pronoun resolution.

Nevertheless, clues indicating the behaviors of different types of pronouns exist. These clues serve as the constraints or conditions for making the resolution decision. A knowledge base can be constructed with these constraints and hence corresponds to a logic network for reasoning. Hence, pronoun resolution can be well described in first-order logic. Also, the use of Markov logic network can support the handling of uncertainties in pronoun resolution.

3.2 First-Order Logic

For reasoning in First-Order Logic, sentences in the knowledge base are formed by atoms and terms. It enables the flexibility of incorporating domain knowledge. It consists of primitives, including constant symbols, function symbols, and predicate symbols. A term is a constant or a variable or a function of n-terms, where an atom is a predicate of n-terms. Constants are considered as objects, variables are ranges of objects and predicates are the mapping of objects to truth values. For example, $P(x)$ is an atom, where P is the predicate, and x is a variable. Sentences are constructed from atoms with connectives and quantifiers.

3.3 Markov Logic Network

Markov Logic Network is proposed by Richardson et al. [1]. It is referred to as a first-order knowledge base with a weight attached to each formula. It combines the representation power of wide variety of knowledge in first-order logic with the advantage of probabilistic model in handling uncertainties.

The probability distribution of a Markov network is:

$$P(X=x) = \frac{1}{Z} exp(\sum_{i}^{F} w_i n_i(x)) = \frac{1}{Z} \prod \phi_i(x_{\{i\}})^{n_i(x)} \tag{1}$$

where w_i is the weight for each formula, i. $n_i(x)$ is the number of true groundings of a formula in first-order logic in the possible world x, and $x_{\{i\}}$ is the truth value of the atoms appeared in the formula, and $\phi_i(x_{\{i\}}) = e^{w_i}$. Z is the normalizer.

In Equation 1, F represents the number of formulae in the corresponding network. A node corresponds to each grounding of the predicates specified in the formulae, and there is an edge between two nodes if their corresponding ground predicates appear together in a formula. As an example, for the following two formulae:

$\forall x \quad drives(x) \Rightarrow has\_car(x) \wedge adult(y)$

$\forall x, y \quad colleagues(x, y) \Rightarrow (drives(x) \Leftrightarrow drives(y))$

In clausal form:

$\neg drives(x) \vee has\_car(x)$

$\neg drives(x) \vee adult(y)$

$colleagues(x, y) \vee drives(x) \vee \neg drives(y)$

$colleagues(x, y) \vee \neg drives(x) \vee drives(y)$

Figure 1 shows a ground network for the above formulae and a finite set of constants, $C = \{\text{Alan}, \text{Ken}\}$. When the formula with weights are given, the

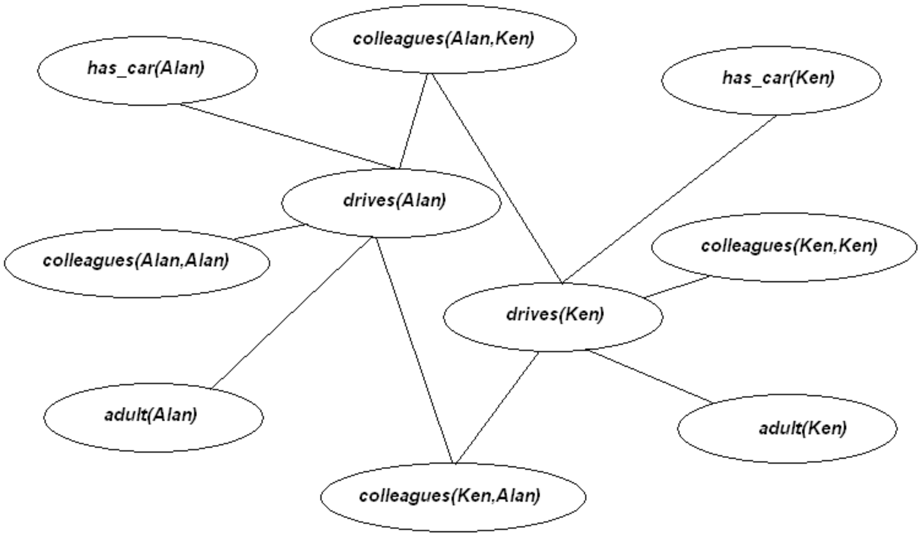

Fig. 1. An example of a ground Markov network

network can be used to infer the probability of the nodes, for example, the probability of whether Ken has a car, given that his colleague, Alan, drives.

4 Problem Formulation

Coreference can be viewed as a relation among entities within texts. The relations are believed to have special characteristics and can be described by constraints and conditions. Those constraints or conditions for pronoun resolution can be formulated into a set of formulae in first-order logic. Pronoun resolution decisions are made on the validation or violation of these formulae.

4.1 Coreference Relation

Coreference linkage can be regarded as the generative process of finding a replacement for a mention in succeeding texts. Suppose we would like to find a coreference for a mention, a corresponding and agreeing pronoun is identified and used in succeeding texts. As an example, when establishing the coreference with a person, a pronoun compatible with the person and the context is selected based on syntactic and semantic constraints. We design a first-order predicate $coref(x, y)$ to represent the coreference linkage between two mentions, x and y.

Pronouns are used when we would like to refer to the same concept by different kinds of mentions. From this process of coreference, some constraints on maintaining the consistency of concept can be deduced. When a mention x corefers with a mention y, the two mentions must have followed some syntactic and semantic constraints. Hence, in solving pronoun resolution, the following formulation is used:

$$\text{syntactic constraints on } x \ \& \ y \Rightarrow x \text{ corefer } y \tag{2}$$

$$\text{semantic constraints on } x \ \& \ y \Rightarrow x \text{ corefer } y \tag{3}$$

where the variable x represents the antecedent candidate, which can be pronouns, nouns, or noun phrases. The variable y refers to the pronouns to be resolved.

This forms the basic idea of our formulation, where predicates for syntactic constraints or semantic constraints will be introduced in Section 4.2.

It is noted that coreference linkages in pronoun resolution are not symmetric:

$$\forall x, y \quad coref(x, y) \neq coref(y, x) \tag{4}$$

In pronoun resolution, the process is to find the corresponding antecedents of each pronoun. Hence, there are two types of constants, pronouns (consequents), and antecedents. The antecedents include all the pronominal, nominal and proper nouns or noun phrases. As a result, some pronouns may be also be the antecedents of some other pronouns. Hence we design an equality predicate, $same(x, y)$, for indicating the pronoun y and the antecedent candidate x, though of different types, are actually the same mention.

Moreover, the dependency between predicates can also be represented in the Markov logic network. For example, the transitivity between coreference links in pronoun resolution can be formulated as:

$$\forall x_1, x_2, y_1, y_2 \quad coref(x_1, y_1) \wedge coref(x_2, y_2) \wedge same(x_2, y_1) \Rightarrow coref(x_1, y_2) \tag{5}$$

The above formulae form the basic relations among mentions, which ensures the validity of the pronoun coreference relations.

Besides the relations related on deciding the existence of the coreference linkage, relations regarding the negative existence of the coreference linkage are also important. We refer these relations as the **negative constraints**. As an example, the negative forms of Equations 2 and 3 are:

$$\neg\text{syntactic constraints on } x \ \& \ y \Rightarrow x \ \neg\text{corefer } y \tag{6}$$

$$\neg\text{semantic constraints on } x \ \& \ y \Rightarrow x \ \neg\text{corefer } y \tag{7}$$

4.2 Syntactic Constraints

In constructing the relations and constraints regarding pronoun resolution, two types of predicates, namely, grammatical and positional predicates, are defined.

Grammatical Predicates

The behavior and the relations between the antecedents of pronouns are highly affected by different types of pronouns. Hence, pronoun types are represented as:

– $personal\_pronoun(y)$ for personal pronouns which can be further classified into three types:

  - $subjective\_pronoun(y)$ for personal pronouns used as the subject. e.g. *I, we, you, he, she, they, it*, etc.
  - $objective\_pronoun(y)$ for personal pronouns used as the object. e.g. *me, us, you, him, her, them, it*, etc.
  - $reflexive\_pronoun(y)$ for personal pronouns which replaces the objective pronoun when referring to the same entity as the subject.
- $possessive\_pronoun(y)$ for pronouns used when it is the possessor of another noun. e.g. *my, our, mine, ours, hers, his, yours, theirs, its*, etc.
- $relative\_pronoun(y)$ for pronouns used when referring back to the noun or noun phrase previously mentioned.
- $noun\_phrase(y)$ for indicating the candidate is a noun phrase.

Positional Predicates

Positional information regarding the pronouns and their antecedent candidate are defined as:

- **Paragraph distance**: the predicate $same\_paragraph(x, y)$ represents that the two nouns are in the same paragraph.
- **Sentence distance**: the predicate $same\_sentence(x, y)$ represents that the two nouns are in the same sentence.
- **Relative position**: the predicate $precedes(x, y)$ represents that the noun x precedes noun y.

With the above predicates, constraints for pronoun resolution can be constructed.

cCommand Constraints

Unlike noun phrase coreference, matching features are not the most influential factor for pronoun resolution. Instead, theories concerning pronouns provide clues in governing the pronoun behavior. The binding theory [2] provides some principles on pronoun interpretation, and defines the relations between two nouns.

- A non-reflexive pronoun should be free within its local domain.
- A reflexive pronoun should be bound within its local domain.

For example: The cat did *it itself*.

The pronoun *it* cannot be coreferent with *the cat*, while *itself* certainly means *the cat*. Through the binding theory, the two coreference linkages can be deduced.

For defining the binding theory, a noun n_1 is said to bind another noun n_2 if and only if (1) n_1 c-commands n_2 (2) n_1 and n_2 are coindexed. C-command represents the relation between two nodes in a parse tree. n_1 is said to c-command n_2 if and only if the first branching node that dominates n_1 also dominates n_2. The c-command prevents coreference between a c-commanding noun phrase with a c-commanded noun phrase, except when it is a reflexive pronoun. The $cCommands(x, y)$ predicate represents the relation that x c-commands y.

With the above definitions, the constraints can be described by the following formulae using the $cCommands(x, y)$ predicate and grammatical predicates:

– Non-reflexive pronouns

$$\forall x, y \quad pronoun(y) \wedge \neg cCommands(x, y) \wedge coindexed(x, y) \Rightarrow coref(x, y) \tag{8}$$

– Reflexive pronouns

$$\forall x, y \quad reflexive\_pronoun(y) \wedge cCommands(x, y) \wedge coindexed(x, y) \Rightarrow coref(x, y) \tag{9}$$

Moreover, the negative form of the above formulae are included for indicating the non-existence of a coreference linkage. The **negative constraints** for syntactic constraints are:

$$pronoun(y) \wedge cCommands(x, y) \wedge coindexed(x, y) \Rightarrow \neg coref(x, y) \tag{10}$$

$$reflexive\_pronoun(y) \wedge \neg cCommands(x, y) \wedge coindexed(x, y) \Rightarrow \neg coref(x, y) \tag{11}$$

For pronoun resolution, it is apparent that these syntactic constraints are the most crucial factors governing the coreference linkages.

Filtering Constraints

In MLN, formulae with finite weight can be regarded as constraints in capturing the possibilities of those conditions, while formulae with infinite weight are hard constraints. They can be regarded as filtering constraints in ensuring the violation of these constraints will cause the query to have zero probability.

The addition of formulae with infinite weight serves as a filtering process, which is usually performed as a separate step in other pronoun resolution algorithms. Hence for handling pronoun resolution, we have to limit the reference candidate for the pronouns as only the antecedents of the pronouns. The following formula is added to filter out the non-antecedent mentions using the positional predicates.

$$\forall x, y \quad \neg precedes(x, y) \Rightarrow \neg coref(x, y) \tag{12}$$

4.3 Semantic Constraints

Besides syntactic constraints, two nouns have to be semantically compatible for them to refer to the same entity. Despite that pronouns are lack of semantic information, two kinds of information, Gender and number, can be obtained from their definitions. And these information about the mentions provides important clues to whether two mentions agreed semantically.

In our pronoun resolution formulation, three types of gender are used: masculine, feminine, and neutral, and two types of number information are used: singular, plural. The two types of information are specified using the predicates, $gender(x, a)$ and $number(x, b)$, respectively. Variable x refers to the pronouns or antecedents, where variable a refers to the three gender types, and variable b

refers to the two number types. $gender(x, a)$ indicate that x is of gender type a, and $number(x, a)$ indicate that x is of number type b.

The recognition of gender and number types for pronouns is relatively straightforward. Pronouns can be classified into gender-specific or gender-neutral. For gender-specific pronouns, they can be further classified into three gender types: masculine(*he/him*), feminine(*she/her*) and neuter(*it*). Gender-neutral pronouns refer to those pronouns which did not distinguish the gender(*you, they*). And all pronouns are well defined to be either singular or plural.

However, the recognition of gender and number types for other noun phrases involves a lot of background knowledge and uncertainties. We employ the noun gender and number data developed by Bergsma, et al. [14]. The corpus is generated from a large amount of online news articles by using web-based gender-indicating patterns. It contains the numbers of times a noun phrase is connected to a masculine, feminine, neutral and plural pronoun. With this corpus, we obtain the gender and number information by matching the noun phrases..

The semantic constraints are hence defined as:

$$gender(x, a) \wedge gender(y, c) \wedge a = c \Rightarrow coref(x, y) \tag{13}$$

$$number(x, b) \wedge number(y, d) \wedge b = d \Rightarrow coref(x, y) \tag{14}$$

and the negative constraints are:

$$gender(x, a) \wedge gender(y, c) \wedge a \neq c \Rightarrow \neg coref(x, y) \tag{15}$$

$$number(x, b) \wedge number(y, d) \wedge b \neq d \Rightarrow \neg coref(x, y) \tag{16}$$

5 Experiments

5.1 Experimental Setup

We have conducted experiments to evaluate our proposed model. The coreference chains obtained are evaluated. We used the noun coreference ACE 2004 data corpus for our experiments. The dataset is split into training and testing datasets randomly. We used 159 articles and 44 articles from the broadcast news (BNEWS) source as training and testing datasets respectively. We consider only the true mentions annotated in the ACE corpus. For c-command predicate generation, the Charniak parser [18] is used for generating the parse tree.

As pronouns can corefer with pronouns and hence a coreference chain will be formed. We would like to evaluate the coreference chains formed in addition to the individual coreference links between pronouns and their antecedents. Hence, the results are evaluated using recall and precision following the standard model-theoretic metric [19] adopted in the MUC task. This evaluation algorithm focuses on assessing the common links between the true coreference chain and the coreference chain generated by the system output.

The Alchemy system [20], which provides algorithms in statistical relational learning on the Markov Logic Networks, was used in our experiments. Discriminative learning are adopted for weight learning during training.

5.2 Results

The results are depicted in Table 1. Since MLN has the benefits of enabling the incorporation of domain knowledge such as formulae describing relations between coreference links, we carried out experiments using different combination of constraints. Three sets of results are given in Table 1. A baseline experiment is conducted assuming coreference linkage existed if the pronoun and its antecedent are in the same sentence. Next, as mentioned before, negative constraints for deducing the non-existence of coreference linkage can be crucial to pronoun resolution. As a result, we excluded the negative constraints to investigate their influence. Lastly, an experiment with the complete formulation including both the syntactic and semantic constraints is conducted.

Table 1. Performance of Pronoun Resolution on the BNEWS dataset

	Recall	Precision	F-measure
Baseline	33.9%	42.5%	37.7%
Without negative constraints	46.1%	45.0%	45.5%
With the negative constraints	56.5%	47.2%	51.4%

The performance results in the last row demonstrate that the resolution performance can be greatly improved in recall and precision with the semantic and syntactic constraints, including their negative constraints. The second row shows the experimental results on excluding the use of negative constraints. The decrease in performance with respect to the second row demonstrates that the negative constraints are also critical in the pronoun resolution formulation with MLN, as inferencing on the decision of not having a coreference link is equally important to the decision of having a coreference link. From analyzing the system generated coreference links, it is observed that as BNEWS contains transcripts for spoken dialogues, extra consideration should be carried on the coreference linkage within conversation by different persons.

6 Conclusions and Future Work

In this paper, we have investigated the application of Markov Logic Network on the resolution of pronoun coreference. The experiments show the characteristics of the formulation of pronoun resolution with Markov logic network in modeling dependencies between entities. It provides an encouraging direction on coreference and cohesion resolutions. Linguistic experts have long been studying the relation between entities in language. Coherence of a text must be maintained for language understanding. And for a text to be coherent, cohesion must be maintained. Textual cohesion refers to the focus of entities or concepts in texts for readers. Strong relations existed between textual cohesion and coreference. Cohesion strategies can be followed using parallelism and dependency. These cohesion cues are crucial for coreference resolution, especially on nominal and pronominal coreference. Heuristic approaches have been mostly employed for incorporating these cohesion cues [21]. These cues can be well represented in first-order logic representations, and will be beneficial by the probabilistic characteristics in Markov Logic Network.

Also, detailed analysis on the strategies governing the referential linkages between noun phrases are proposed by many linguistic experts. The binding theory proposed by Chomsky [2] is one of the well know model. The binding theory provides well defined syntactic constraints to coreference resolution. The c-command concept is currently implemented in our system as a binary predicate. But as determining the binding among noun phrases is not a straightforward task, the uncertainties can be handled through the use of MLN. Moreover, we believe by further investigating the features or relations best suited to the logic network, the performance could be further improved.

Our future directions include further investigating the incorporation of cohesion cues in Markov logic network for coreference resolutions, and further expanding the coreference resolution on not only pronoun resolution, but also nominal and proper noun coreference resolutions.

Acknowledgement

The work described in this paper is substantially supported by grants from the Research Grant Council of the Hong Kong Special Administrative Region, China (Project Nos: CUHK 4179/03E, CUHK4193/04E, and CUHK4128/07) and the Direct Grant of the Faculty of Engineering, CUHK (Project Codes: 2050363 and 2050391). This work is also affiliated with the Microsoft-CUHK Joint Laboratory for Human-centric Computing and Interface Technologies.

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