1 Problem Overview

Consider “Google-Phone” where users are given a free service to call each other over the Internet. Google is looking for a method to provide a practical profit model for this service. Alice proposes using Google’s existing model of using advertisements to generate revenue. Google is going to provide on-line advertisements as a conversation progresses. The current approach used by Google is to do a very simple count of the most highly appearing nouns. Then, the corresponding advertisements are attached to each appearing noun.

Bob proposes using a less naive approach to this problem. He notices that conversations do not have repetitions of the keyword nouns but rather pronouns that refer to previously spoken subjects. Impressed by Bob’s observation, Google decides to develop techniques to address Bob’s observations.

To better understand the complexity involved in this problem, consider the following example:

**Shyam:** This sucks, it’s snowing outside.

**Grace:** Tell me about it! I parked my BMW outside and my windshield got cracked because of the cold!

**Shyam:** I’m so sorry! Did you get it fixed?

**Grace:** No it’s going to take at least a week.

**Shyam:** Well, do you know of a good place to fix it?

This natural conversation supports Bob’s claim that the originating keyword noun actually does not appear often. Further, if Google desires to give meaningful advertisement, it needs to understand whether the pronoun “it” in this conversation refers to the keyword-noun: “BMW” or the keyword-noun: “windshield”. That is, given a set of contextual sentences, Google must figure out the most referred-to keyword-noun.
2 Prior Work

Much previous work [2, 3, 4, 5, 6] on pronoun disambiguation has been presented in reference to understanding how humans associate a noun to a pronoun in context. The existing work may be generally divided into two domains: (1) figuring out the pronoun association within a sentence and (2) figuring out the pronoun association across sentences. Since the problem dictates the need for both of these associations, the goal in this project is to review these works and understand how well a practical system might work.

One clear class of works falls into the category known as clustering. This clustering is based on an observation that humans group noun phrases into different categories. This is generally known as noun phrase resolution. The goal of this class of works is to cluster these noun phrases into groups in a similar manner. This is usually done by defining some rules, e.g. inanimate, animate, characterization of the head noun, etc. Following the success of these clustering methods, the binding of pronouns should gracefully follow.

Clustering does not perform particularly poorly. However, in our problem, we are interested in looking at natural discourses. In these cases, there are several distinct characteristics about natural discourses which are not exploited in clustering methods. We don’t discuss them in detail here, but to give a taste here, interjections such as ”anyway!” or ”but, whatever!” provide some hint toward a change of topic. This is useful in the clustering techniques, but even more useful in the method that we present.

Another class of models offer a statistical approach toward obtaining a computational model of discourse. These are also interesting. However, it is not yet generally agreed that these automatic learning-systems perform as well as a state of the art non-learning system. As we will discuss in the final section of this report, these statistical approaches are ultimately necessary in fine-tuning. However, for the problem that we are interested in, a tradeoff in complexity should be considered.

Overall, a large number of prior works exist in this area. In this project, we understand what the approach in these works are and how we might use some of the methods in what we present.

3 Our Approach

In order to provide google with a simple practical pronoun disambiguation scheme we take a linguistic approach, by trying to understand the different linguistic properties of the natural language, we determine rules for ways in which pronouns can be disambiguated to produce higher accuracy hits.

In general, a pronoun should only have one antecedent.

The goal of the method is to be able to bind a pronoun to the correct antecedent. The most commonly used methods operate using gender and object disambiguation methods. Our approach supports this. Additionally, we consider the nature of the natural discourse and consider cases where gender disambiguation might not be enough.

One thing to point out is that there are general grammatical rules for how to use pronoun disambiguation. However, since we are considering a conversational discourse, it is not necessarily appropriate to design according to classic grammatical rules. For example, classic grammatical rules indicate that one should use the pronoun ”it” consistently. However, in natural discourse, the pronoun ”it” might be used multiple times to refer to many different antecedents.

In some cases, this consideration actually helps us. For example, in a natural conversation,
interjections such as "Anyway" might signify a change in topic and a flush of the buffer of possible antecedents. In other cases, considering a natural discourse is more challenging in that there might be multiple references using the pronoun "it".

One way that these challenges may be met is to begin taking account the relationships between nouns and verbs as these are rules that may be exploited cross-contextually. We should think of a method to develop classes of nouns and classes of verbs that may co-exist and not co-exist and use this to disambiguate pronoun-antecedent association with this additional information.

We designed this system in this fashion because we believe that in some sense we learn the same way. That is, we keep a general idea of the nouns that we have heard in the conversation up until encountering a pronoun. Since we understand that some nouns don’t go with some actions, (e.g. a table cannot catch mice but a cat can catch mice) we can automatically disambiguate and create the correct binding when seeing a pronoun.

A few examples to demonstrate the method we present are discussed in this section.

3.1 Gender based disambiguation

Consider the sentence sequence:

My husband visited grandmother. He was happy.

Example1 = [''my husband visited grandmother'',
             ''he was happy'']

Here we have two nouns: “husband” and ”grandmother”. However since the pronoun “he” denotes a male, it can only be associated with the “husband”.

3.2 Human/Non-human based disambiguation

Consider the sentence sequence:

John has a cat. It jumped over the fence.

Example2 = [''John has a cat'','
             'It jumped over the fence'']

Again, we have two nouns, “John” and “cat”. However, since the pronouns “it” are not in general used for humans, “it” can only be associated with the noun “cat”.

3.3 Noun-Verb-association based disambiguation

Consider the sentence sequence:

The kids wore skirts. They moved to the apartment.

Example3 = [''the kids wore skirts'','
             'they moved to the apartment'']

Here we have two nouns, “kids” and “skirts”. However, since “skirts” cannot move on their own to the apartment, “they” here refers to “kids”.

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Consider the sentence sequence:

The men all wore slacks. They were starched.

Example4 = ['''the men all wore slacks''',
            '''they were starched''']

Here we have two nouns, “men” and “slacks”. However, the sentence, ”They were starched” is a passive form which implicitly means ”They were starched (by someone)”. Again since “men” cannot be starched by someone by slacks can be, “they” here refers to “slacks” (the object).

3.5 Locality disambiguation

Consider the sentence sequence:

Mother came home from the store. Grandmother was sitting at home. She was happy.

Example5 = ['''mother came home from the store''',
            '''grandmother was sitting at home''',
            '''she was happy''']

Here, there are two subjects: mother and grandmother. Technically, this example could not occur in a document strictly governed by classical grammar. However, in natural discourse, this type of conversation often arises and it is clear what the ”she” pronoun refers to. In these moments of ambiguity, we take the noun most recently added to the buffer, in this case: ”grandmother”.

3.6 Change of Context

Consider the sentence sequence:

The men all wore slacks. They were starched. Anyway... The kids wore skirts. They moved to the apartment

Example6 = ['''the men all wore slacks''',
            '''they were starched''',
            '''anyway''',
            '''the kids wore skirts''',
            '''they moved to the apartment''']

Here, the word “anyway” usually means that the context has changed. Thus, the context must be changed at the encounter of such context-change words.

However, people also use “anyways” to refer to some change in mood. For example, consider the following sentence sequence:

The men all wore slacks. There were starched. Anyway... They were torn
Example7 = ['''the men all wore slacks''',
    '''they were starched''',
    '''anyway''',
    '''they were torn''',
]

Here although we have encountered the word, anyway, it only indicates a partial change of context.

4 How to make it work

To implement a proof of concept for pronoun disambiguation, we need to neatly stitch the above rules so that we can produce a system which can smoothly handle all the above cases. We begin by describing how we maintain the various nouns we encounter during the discourse.

4.1 Framing the Context

In order to do pronoun disambiguation, we need a list of nouns which have occurred before the pronoun in consideration. As shown in Figure 1, we maintain a context frame, which stores the noun forms and how many times we believe, each of the noun has occurred. Consider the following example whose context frame is depicted in the figure.

John met Dorothy in the School.
He fell in love with her.
She was not interested.

Here we have three nouns: John, Dorothy and School. Since the pronoun “he” refers to John and the pronouns “her”, “she” refers to Dorothy, the context frame for this group of sentences, need to have three entries: John, Dorothy and School with their associated number of occurrences.

4.2 Pronoun Classification

In order to be able to apply the Gender and Human/NonHuman Disambiguation rules we need to classify the pronouns into categories to help us apply these rules. The following is the classification we use.
MALE_PRONOUNS = ['he', 'him', 'his', 'himself']
FEMALE_PRONOUNS = ['she', 'her', 'hers', 'herself']
HUMAN_SEXLESS = ['their', 'theirs']
HUMAN_NEUTRAL = ['we', 'me', 'mine', 'yourself', 'yourselves', 'our', 'ours', 'yourself', 'ourselves', 'myself', 'myself', 'ours', 'ourself', 'ours', 'us', 'ours', 'yours', 'ours', 'I']
NEUTRAL = ['them', 'they', 'there']
NON_HUMAN = ['it', 'its', 'itself']

Clearly, pronouns like “he” must denote males and “she” must denote females. In addition, pronouns like “they” and “them” are gender neutral and can also be used for objects and animals. Pronouns like “it” are non-human pronouns since they cannot to describe humans.

4.3 Noun-Verb Association

The main contribution of this work is to use Noun and Verb association in order to disambiguate the pronouns.

4.3.1 Classifying Noun and Verb

In order to understand why need to classify nouns and verbs, let us consider the following example.

The cat was on the table.
He jumped on the floor.

Here we have two nouns in the context frame before the occurrence of “he”. We begin by replacing “he” by each of the entries in the context frame.

cat jumped on the floor.
table jumped on the floor.

Humans can easily figure out that there is something wrong with the later sentence. This can be hypothesized to be because, tables are non-living entities which cannot act on their own whereas cat are living entities which can act on their own. Similarly there are certain classes of verbs that can be associated with only certain classes of nouns

We use this intuition to form classes for the nouns and verbs. Wordnet: http://wordnet.princeton.edu already does this classification for a considerably big corpus of parts of speech. These classification are known as lexical descriptions within wordnet. Thus for each description noun and description verb, we create a table of the likelihood of these two forms being associated. For each noun and verb, there is lexical file information associated with the word. We use this information at a higher level to create generalizations about subjects, objects and actions.

There are all together at the time of this project, 25 noun types and 15 verb types. The nouns lexical types we used are listed here:

<table>
<thead>
<tr>
<th>Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>03</td>
<td>noun.Tops unique beginner for nouns</td>
</tr>
<tr>
<td>04</td>
<td>noun.act nouns denoting acts or actions</td>
</tr>
<tr>
<td>05</td>
<td>noun.animal nouns denoting animals</td>
</tr>
<tr>
<td>06</td>
<td>noun.artifact nouns denoting man-made objects</td>
</tr>
<tr>
<td>07</td>
<td>noun.attribute nouns denoting attributes of people and objects</td>
</tr>
<tr>
<td>08</td>
<td>noun.body nouns denoting body parts</td>
</tr>
<tr>
<td>09</td>
<td>noun.cognition nouns denoting cognitive processes and contents</td>
</tr>
<tr>
<td>10</td>
<td>noun.communication nouns denoting communicative processes and contents</td>
</tr>
<tr>
<td>11</td>
<td>noun.event nouns denoting natural events</td>
</tr>
</tbody>
</table>
And the verbs we used are listed here:

29 verb.body verbs of grooming, dressing and bodily care
30 verb.change verbs of size, temperature change, intensifying, etc.
31 verb.cognition verbs of thinking, judging, analyzing, doubting
32 verb.communication verbs of telling, asking, ordering, singing
33 verb.competition verbs of fighting, athletic activities
34 verb.consumption verbs of eating and drinking
35 verb.contact verbs of touching, hitting, tying, digging
36 verb.creation verbs of sewing, baking, painting, performing
37 verb.emotion verbs of feeling
38 verb.motion verbs of walking, flying, swimming
39 verb.perception verbs of seeing, hearing, feeling
40 verb.ownership verbs of buying, selling, owning
41 verb.social verbs of political and social activities and events
42 verb.stative verbs of being, having, spatial relations
43 verb.weather verbs of raining, snowing, thawing, thundering

4.3.2 Uncovering Objects and Subjects: Sentence Parsing

Why do we need to know why whether an pronoun appears as an object or a subject?

Suppose the context frame consists of the nouns, [table, dog]. Suppose we see the following sentence now.

It is moved to the corner

Here “it” can either refer to the table or the dog, whereas if we encounter the following sentence

It moved to the corner

Here “it” can only refer to the dog.
How do we differentiate between these two cases? The key is that the first sentence is a passive sentence and “it” is a object (it is moved by someone), whereas, the second sentence is a active sentence where “it” is a subject.

Thus our disambiguation relies on the parsing structure of each sentence to determine (1) the parts of speech, (2) passive or active tone of the sentence, (3) subject and object determination. In order to do the parsing we use the switchboard corpus to learn the rules.

How do we classify each noun as either a subject? in context or an object in context. Since the pronoun disambiguation relies on the bindings between dictionary objects as referenced in Wordnet, it is important to distinguish between an active and passive sentence. This is where we extract whether a noun is a subject or an object. The subject and object determination is based on a simple observation of the parsing structure that the subject comes in general before the object unless the sentence is in the passive.

There are generally a few rules to likely determine whether a sentence is active or passive. We may generalize the rules as:

1. The verb is a form of the verb 'be'
2. There is a morphological ending at the end of a verb, i.e. 'ed', 'en' etc.
3. There is no sentence predicate

There are in general only a few verbs of the form 'be'. Here, we implemented: [was, were, been]. There are only a few exceptions to this rule and we do not consider them here. Verbs with a morphological ending 'ed', these are very rare and we do not consider them here as most of them are encompassed by rule three where the sentence predicate is implied in a passive sentence. One example is in Figure 2 where the ‘ed’ ending removes the ability of the verb to case mark.

4.3.3 Noun-Verb Association Rules

Now that we have the different classifications for the nouns and the verb along with information about whether the accordance of the noun is an object and the subject, how do we use this information?

From the information, we may begin to make ‘valid’ and ‘invalid’ associations. For example, it is clear that verbs in the class verb.perception may not be associated with nouns in the class noun.food. We incorporate the object/subject to further narrow down the associations. For example, nouns in the class noun.animal can be associated with verbs in the class verb.motion both as a subject and a object, but nouns in the class noun.object which are natural objects can be associated with verbs in the class verb.motion only as a object. We use this information to create a binary three-dimensional matrix of associations between the noun-class, verb-class and subject-object.

4.4 Partial Context Change

Finally, how do we implement the context change rules, when context change words like anyways occur? As described in the approach section, the context change words like “anyways” do not mean a complete change of context, always. So, we need to provide for a mechanism to capture this partial change of context.
Figure 2: Tree graph where there is no predicate

Figure 3: Partial change of context in the presence of context-change words
We do it by maintaining two *context frames*: the current frame and the old frame, as shown in Figure 3. Whenever we encounter a sentence with the context-change words like 'anyways', we copy the entries in the current frame into the old frame and flush the current frame. However, to account for the partial change of context, whenever entries in the current list fail to produce any associate, we check for a match in the old frame. If there is a match, we promote the entry with the maximum count to the current frame, to ensure that it is in the current context.

5 Discussion and Future Work

We have implemented an initial prototype of our rule based pronoun disambiguation. However, there is a huge scope for making this system extremely accurate.

- The three-dimensional association matrix we have used right now is a 0-1 matrix. However, what would be really useful is a probabilistic matrix, where each entry is a the probability of the association. One could potentially get this association by parsing a huge corpus of sentences. This kind of a probabilistic matrix can really help us disambiguate in the case of ties.

- The classes for the nouns and the verbs, used by us are picked from the classes and the corpus from the Wordnet database. Unfortunately, the classes in the wordnet corpus as too broad which prevents precise association rules. One could potentially create narrower classes which could capture this association in a better way.

- Consider the sentences of the following form.

  Did u go to the movie?
  It is none of ur business.

  Here *It* refers to the event of ”going to the movie”. Although this kind of pronoun usage is prohibited by classical grammar[1], this usage is common in colloquial English. We need to design more intelligent rules in order to handle this kind of references.

- In this project we use the association between nouns and verb in order to narrow down on the noun choices. However, one can potentially use adjectives to further narrow down on the choices. For example consider the following sentence

  The girls are wearing skirts.
  They are colorful.

  Here 'They' refers to the skirts since the adjective 'colorful' is not in general associated with 'girls' but with objects, 'skirt'. One could potentially create classes for adjectives and creates association rules between adjectives and noun. We refrain from doing this in this project since Wordnet currently provides only one class for adjectives, which is not that helpful.

6 Run-time Notes

- Make sure that the parsed switchboard corpus is available in your repository of default parsed training corpus. That information is available as swbd.tar.gz. Place the resulting .mrg files
in the default training library for NLTK. For us, this was: /usr/share/nltk/data/corpora/treebank/combined/

- Running python test.py will give a taste of some of the examples.

- Trying other examples: Set the parameters grammar equal to one of the corpus dictionary to get things running quickly and the parameter sentences equal to one of the Example sentence sequences. By default, they are set to Example2.

Running test.py without your own input should give some output like this:

*****Summary*****

Original sentences:
['the kids wore skirts', 'they moved to the apartment']

New sentences with pronoun bindings
['the kids wore skirts ', 'kids moved to the apartment ']

6.1 Data File Descriptions

The main pieces of code which we implemented are in cathelper.py and pnhelper.py where the referred-to functions are commented and the code itself is commented. test.py serves only as wrapper code for these two main files. The following is a brief description of the data files that are reference and created (aside from the switchboard corpus files).

- oXX: These files contain the object noun to verb relationship possibilities as extracted from wordnet.com.
- sXX: These files contain the subject noun to verb relationship possibilities as extracted from wordnet.com.
- data.name.female and data.name.male: These files refer to proper Female and proper Male names for disambiguation.
- data.noun refers to the lexical information of a noun as extracted from wordnet
- data.verb refers to the lexical information of a verb as extracted from wordnet

References

[3] Claire Cardie, “Corpus-Based Acquisition of relative pronoun disambiguation heuristics”.

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[4] Steven B. Greene, Gail McKoon and Roger Ratcliff, “Pronoun Resolution and Discourse Models”.

