

Faculty of Engineering and Computing

Natural Language Processing

**NLP - Assignment**

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# Proposed NLP Design Enhancements - The Goals

## Goal 1 Anaphoric resolution: Description and design

Anaphoric resolution, also known as anaphora resolution, is an important aspect of natural language understanding. It involves identifying and resolving the referents of pronouns and other referring expressions in a text. The process of anaphoric resolution helps in understanding the relationships between different entities within a text, which is crucial for accurate natural language processing (NLP) [1].

### 3.1.1. Proposed NLP Technique

For the anaphoric resolution task, we propose using a rule-based approach combined with machine learning techniques to accurately resolve anaphoric expressions. Rule-based approaches have shown promising results in various NLP tasks, and they can be particularly effective when combined with machine learning techniques [2]. We will employ the Stanford CoreNLP library [3], which includes a state-of-the-art anaphoric resolution system called the "deterministic coreference resolution system" [4]. This system utilizes a set of hand-crafted rules and machine learning classifiers to resolve anaphoric expressions with high precision.

### 3.1.2. Algorithm and Processing Steps

The algorithm for anaphoric resolution can be broken down into the following steps:

1. Preprocessing: Tokenize the input text and perform part-of-speech (POS) tagging and dependency parsing using the Stanford CoreNLP library. This will help in identifying the grammatical structure and relationships between words in the text.
2. Pronoun Identification: Identify pronouns and other referring expressions in the text. This can be achieved by analyzing the POS tags and dependency relations obtained during preprocessing.
3. Candidate Antecedent Selection: For each identified pronoun, select a set of candidate antecedents. Candidate antecedents are the nouns or noun phrases that could potentially refer to the pronoun in question. The selection process can be guided by a set of linguistic rules, such as those proposed by Lappin and Leass [5], which consider factors like syntactic constraints, agreement features (e.g., gender, number), and discourse salience.
4. Feature Extraction: Extract relevant features from the candidate antecedents and the pronoun. These features may include syntactic, semantic, and discourse-related features, such as the grammatical role of the antecedent, the semantic similarity between the antecedent and the pronoun, and the position of the antecedent in the text.
5. Classification: Train a machine learning classifier, such as a support vector machine (SVM) or a neural network, to predict the correct antecedent for the pronoun based on the extracted features. The classifier can be trained on a labeled dataset of texts with annotated anaphoric expressions.
6. Resolution: For each pronoun, select the candidate antecedent with the highest classification score as the resolved referent. Update the input text by replacing the pronoun with its resolved referent.

### 3.1.3. Data Requirements and Data Structures

To implement the anaphoric resolution algorithm, the following data and data structures are required:

1. Labeled Dataset: A dataset of texts with annotated anaphoric expressions is needed to train the machine learning classifier. Examples of such datasets include the OntoNotes corpus [6] and the MUC-6 and MUC-7 coreference datasets [7].
2. Feature Vectors: A data structure for storing the extracted features from candidate antecedents and pronouns. This can be a simple list or an array.
3. Classifier Model: A trained machine learning model for predicting the correct antecedent based on the feature vectors. The model can be saved as a file and loaded during runtime.
4. Dependency Graph: A data structure for representing the dependency relations between words in the text. This can be obtained using the Stanford CoreNLP library and will be used during candidate antecedent selection and feature extraction.
5. Anaphora Resolution Module: A module that encapsulates the anaphoric resolution algorithm and exposes functions for performing anaphora resolution on the input text. This module should be designed to be easily integrated with the existing chatbot code.

## 3.2. Goal 2 Prepositional Phrase-Attachment Resolution: Description and Design

Prepositional phrase (PP) attachment resolution is a critical task in natural language understanding that involves determining the correct attachment of a prepositional phrase to its preceding constituents, such as a verb or a noun. Resolving PP-attachment ambiguities is essential for accurately parsing the syntactic structure of a sentence and understanding its meaning [8].

### 3.2.1. Proposed NLP Technique

To address the PP-attachment resolution problem, we propose a hybrid approach that combines rule-based heuristics and machine learning techniques. The rule-based heuristics will be used to filter out some of the most evident PP-attachment cases, while a machine learning model will handle the more ambiguous cases. We will utilize the Maximum Entropy (MaxEnt) model [9], a popular choice for various NLP tasks, including PP-attachment resolution, due to its flexibility and ability to handle a large number of features [10].

### 3.2.2. Algorithm and Processing Steps

The algorithm for PP-attachment resolution consists of the following steps:

1. Preprocessing: Tokenize the input text and perform part-of-speech (POS) tagging and dependency parsing using the Stanford CoreNLP library. This step will help in identifying the grammatical structure and relationships between words in the text.
2. Identification of Prepositional Phrases: Identify prepositional phrases in the text by analyzing the POS tags and dependency relations obtained during preprocessing. A prepositional phrase is a sequence of words that begins with a preposition and is followed by a noun or a pronoun.
3. Rule-based Heuristics: Apply a set of hand-crafted rules to filter out the most evident PP-attachment cases. For example, one rule might be that if the head of the prepositional phrase is a verb, and there is no noun between the verb and the preposition, then the PP should be attached to the verb. These rules can be based on linguistic knowledge and patterns observed in the training data.
4. Feature Extraction: For the remaining ambiguous cases, extract relevant features from the prepositional phrases, the potential head words (verbs or nouns), and the surrounding context. These features may include POS tags, syntactic relationships, word embeddings, and distance measures between the prepositional phrase and the potential head words.
5. Classification: Train a Maximum Entropy model on a labeled dataset of texts with annotated PP-attachments, using the extracted features as input. The MaxEnt model will learn to predict the correct attachment (either verb or noun) based on the feature vectors.
6. Resolution: For each ambiguous prepositional phrase, use the trained MaxEnt model to predict the correct attachment. Update the input text by annotating the resolved PP-attachment.

### 3.2.3. Data Requirements and Data Structures

To implement the PP-attachment resolution algorithm, the following data and data structures are required:

1. Labeled Dataset: A dataset of texts with annotated PP-attachments is needed to train the Maximum Entropy model. Examples of such datasets include the Wall Street Journal (WSJ) Treebank [11] and the Penn Treebank [12].
2. Feature Vectors: A data structure for storing the extracted features from prepositional phrases, potential head words, and the surrounding context. This can be a simple list or an array.
3. MaxEnt Model: A trained Maximum Entropy model for predicting the correct PP-attachment based on the feature vectors. The model can be saved as a file and loaded during runtime.
4. Rule-based Heuristics: A set of hand-crafted rules for filtering out the most evident PP-attachment cases. These rules can be implemented as functions or methods within the code, and they can be easily updated or modified based on linguistic knowledge or patterns observed in the training data.
5. Annotation Data Structure: A data structure for storing the resolved PP-attachments in the input text. This can be a list of tuples, where each tuple contains the start and end positions of the prepositional phrase, the position of the head word (verb or noun), and the type of attachment (verb or noun).
6. To ensure the effectiveness and accuracy of the PP-attachment resolution algorithm, it is crucial to have a diverse and representative training dataset. This dataset should include a wide range of syntactic structures and attachment cases to help the model learn the patterns and generalizations necessary for making accurate predictions.
7. Additionally, the rule-based heuristics should be carefully designed and evaluated on a separate development dataset to ensure their effectiveness in filtering out the most evident PP-attachment cases. Regular updates to the rules based on linguistic knowledge or patterns observed in the training data can help improve the overall performance of the algorithm.
8. Furthermore, the selection of features for the Maximum Entropy model is critical for achieving good performance. It is essential to experiment with different sets of features and perform feature selection techniques, such as forward or backward selection, to identify the most informative features for the task [13].

In conclusion, resolving PP-attachment ambiguities is a crucial step in natural language understanding. By combining rule-based heuristics and machine learning techniques, we can develop a robust and accurate algorithm for PP-attachment resolution that significantly improves the performance of our chatbot in understanding and processing user inputs.

## 3.3. Goal 3 Query the user for their name and remember their name: Description and design

### 3.3.1. Proposed NLP technique

To query the user for their name and remember it throughout the conversation, we propose using a combination of pattern recognition and named entity recognition (NER). This combination will help the chatbot understand when the user is providing their name and store it in a variable for future use in the conversation.

Named Entity Recognition (NER) is an NLP technique that identifies and classifies named entities such as person names, locations, organizations, and dates [14]. In this case, we will use an NLP library like spaCy to identify names within the user's input.

### 3.3.2. Algorithm and processing steps

Detect when the chatbot should ask for the user's name: At the beginning of the conversation or when the chatbot fails to understand a user input, it can ask for the user's name to personalize the conversation.

1. Extract the user's name: Once the user provides their name, use NER from the spaCy library to identify and extract the name from the input text. If multiple names are detected, the chatbot can either use the first one or ask for clarification.
2. Store the user's name: After extracting the user's name, store it in a variable within the chatbot's code, so it can be used later in the conversation.
3. Personalize the conversation: Use the stored user's name to personalize the chatbot's responses by incorporating the name in the generated text. This can be done by adding placeholders in the response templates and replacing them with the user's name when generating the response.
4. Remember the user's name throughout the conversation: Maintain the stored name in a variable for future use in the conversation, so the chatbot can continue to provide personalized responses.

### 3.3.3. Data requirements and data structures

To implement this goal, we require the following data structures:

1. A variable to store the user's name: This variable should be accessible throughout the chatbot's code, allowing it to be used in generating personalized responses.
2. Named entity recognition (NER) model: A pre-trained NER model, such as the one provided by the spaCy library, to identify and extract the user's name from the input text.

In summary, asking for and remembering the user's name can enhance the user experience by personalizing the conversation. By combining pattern recognition with NER techniques, the chatbot can effectively identify and store the user's name, resulting in a more engaging and human-like interaction.

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