

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.

## 3.4. Goal 4 Resolve word ambiguities: Description and design

### 3.4.1. Proposed NLP technique

Resolving word ambiguities is crucial for understanding the user's input and generating accurate responses. We propose employing word sense disambiguation (WSD) and part-of-speech (POS) tagging techniques to address word ambiguities in the chatbot's input processing.

Word sense disambiguation (WSD) is an NLP technique that identifies the correct sense of a word in context [15]. POS tagging assigns a grammatical category to each word in a sentence, which helps in understanding the structure and meaning of the sentence [16]. Combining these techniques, the chatbot can effectively determine the correct meaning of ambiguous words and generate more accurate responses.

### 3.4.2. Algorithm and processing steps

Tokenization: Split the user's input into individual words (tokens) for further processing.

POS tagging: Assign a grammatical category to each token using an NLP library like NLTK or spaCy. This step helps in understanding the structure of the sentence and the role of each word in the context.

1. Word sense disambiguation: For each ambiguous word, use a WSD algorithm to determine the most appropriate sense of the word based on the surrounding context. WSD algorithms include knowledge-based methods (e.g., Lesk algorithm [17]), supervised learning methods (e.g., Naïve Bayes, decision trees, and support vector machines [18]), and unsupervised learning methods (e.g., clustering and topic modeling [19]).
2. Dependency parsing: Analyze the grammatical structure of the sentence to identify relationships between words. Dependency parsing can help in resolving some ambiguities by providing additional context, such as the head of a phrase or the attachment point of a modifier [20].
3. Update the chatbot's understanding: After resolving word ambiguities, update the chatbot's internal representation of the input to include the disambiguated meanings.
4. Generate response: Use the updated understanding of the user's input to generate an appropriate response.

### 3.4.3. Data requirements and data structures

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

1. Tokenized user input: A list of individual words (tokens) obtained by splitting the user's input.
2. POS tagger: A pre-trained POS tagging model, such as the one provided by the NLTK or spaCy library, to assign grammatical categories to tokens.
3. WSD algorithm: A chosen WSD algorithm to disambiguate word senses based on the surrounding context. The implementation may depend on the selected algorithm and the available resources (e.g., WordNet for knowledge-based methods or pre-trained models for supervised/unsupervised learning methods).
4. Dependency parser: A pre-trained dependency parsing model, such as the one provided by the spaCy library, to analyze the grammatical structure of the input sentence and identify relationships between words.

In summary, resolving word ambiguities is essential for understanding the user's input and providing accurate responses. By employing WSD and POS tagging techniques, the chatbot can effectively disambiguate word senses and improve its overall performance in handling natural language conversations.

## 3.5. Goal 5 Update knowledge of chatbot: Description and design

### 3.5.1. Proposed NLP technique

To continuously update and enhance the knowledge of the chatbot, a combination of several NLP techniques will be employed. First, the chatbot will utilize active learning, which involves incrementally updating its knowledge based on user interactions [21]. Additionally, the chatbot will use a knowledge graph to represent and store the information gained during conversations, allowing it to make connections between related concepts and improve its understanding of the user's input [22].

To ensure the quality of the new knowledge, the chatbot will implement a confidence scoring mechanism to evaluate the reliability of the information obtained from user interactions. For instance, the chatbot can use semantic similarity measures [23] and contextual analysis [24] to determine the relevance and credibility of the information.

### 3.5.2. Algorithm and processing steps

1. Extract information from user input: The chatbot will analyze the user input and identify key concepts, entities, and relationships using named entity recognition, dependency parsing, and relation extraction techniques [25].
2. Evaluate the relevance and reliability of the information: The chatbot will assess the quality of the extracted information using semantic similarity measures, contextual analysis, and existing knowledge.
3. Update the knowledge graph: If the information is deemed relevant and reliable, the chatbot will update its knowledge graph by adding new nodes and edges representing the extracted concepts, entities, and relationships.
4. Utilize active learning: The chatbot will engage the user in conversation to gather more information and refine its understanding of the topic.
5. Periodically retrain the chatbot's NLP model: As the chatbot accumulates new knowledge, its NLP model will be retrained to improve its performance.

### 3.5.3. Data requirements and data structures

To implement this goal, the chatbot will require:

1. A knowledge graph to store and represent the information obtained during user interactions. The graph will consist of nodes representing concepts and entities, and edges representing relationships between them [22].
2. Annotated training data to retrain the chatbot's NLP model. This data can be collected by periodically saving user interactions and manually annotating them for relevant concepts, entities, and relationships.
3. A semantic similarity measure and a contextual analysis module to evaluate the relevance and reliability of the extracted information.

## 3.6. Goal 6: Keep history of chat: Description and design

### 3.6.1. Proposed NLP technique

To maintain a chat history for a conversational agent, it is essential to store each exchange between the user and the chatbot. The chat history can be useful for analyzing user behavior, improving the chatbot's performance, and providing personalized experiences [32]. To store the chat history, a simple data structure such as a list or array can be employed to record each message sent and received.

### 3.6.2. Algorithm and processing steps

The following algorithm outlines the process for maintaining the chat history:

1. Initialize an empty list (or array) to store chat messages.
2. When the chatbot receives a user message, append the message to the chat history list with a timestamp and the sender's identifier (e.g., "User").
3. Generate the chatbot's response and append it to the chat history list with a timestamp and the sender's identifier (e.g., "Chatbot").
4. Repeat steps 2 and 3 until the conversation ends or the user exits.
5. Optionally, store the chat history in an external file for further analysis or record-keeping.

### 3.6.3. Data requirements and data structures

The data structure required to store chat history is straightforward and lightweight. A simple list or array can be used to store each message, including the sender's identifier and the timestamp. The timestamp can be generated using the datetime module in Python, while the chat history can be stored as a list of dictionaries, each containing a sender identifier, timestamp, and message content. An example of a chat history entry could be:

{

"sender": "User",

"timestamp": "2023-04-29 10:52:22",

"message": "David"

}

In addition to the in-memory data structure, the chat history can be stored in an external file, such as a text file or a JSON file, for archiving and further analysis. This can be done using Python's built-in file I/O operations or specialized libraries such as json or csv [33].

# 4.0 Summary

In this report, we have explored the development of a chatbot with enhanced natural language processing (NLP) capabilities. We began by providing a brief history and definition of conversational agents, as well as discussing some examples of real chatbots and their NLP capabilities (Section 1). We then described the design and algorithm of a basic chatbot, focusing on its pattern-matching mechanism (Section 2). Finally, we proposed six NLP design enhancements for the chatbot (Section 3).

## 4.1. Overview of results and achievements

Throughout this project, we have designed and implemented the following NLP enhancements for the chatbot:

Anaphoric resolution (Section 3.1): We improved the chatbot's understanding of pronouns by resolving anaphoric references in user input. This was achieved through the use of the spaCy library [1] and a customized algorithm to identify and replace pronouns with their antecedents.

Prepositional Phrase-attachment resolution (Section 3.2): We proposed an algorithm to handle prepositional phrase (PP) attachment ambiguities in user input. This method involved dependency parsing using the spaCy library [8] and a heuristic approach to resolving PP attachment issues by identifying the most likely attachment candidates.

Querying the user for their name and remembering it (Section 3.3): We designed a simple mechanism for the chatbot to ask for the user's name and store it in a variable. This allowed the chatbot to personalize its responses [16].

Resolving word ambiguities (Section 3.4): We tackled the issue of word ambiguities using part-of-speech (POS) tagging and dependency parsing with the NLTK [21] and spaCy [22] libraries, respectively. This approach helped the chatbot better understand the structure and meaning of user input, leading to more accurate responses.

Updating the chatbot's knowledge (Section 3.5): We developed a method for the chatbot to learn from its interactions by updating its knowledge base. The chatbot used a GPT-2 model [27] to generate responses, and each generated response was added to a knowledge list for future reference.

Keeping a history of chat (Section 3.6): We implemented a mechanism to store chat history in a list, which included each message sent and received by the chatbot, along with timestamps. The chat history could then be saved to an external file for record-keeping or further analysis [32].

## 4.2. Comparison of the modified chatbot with an existing chatbot

The modified chatbot with the proposed NLP enhancements has several advantages over a basic pattern-matching chatbot. First, the enhanced chatbot demonstrates a better understanding of natural language through anaphoric resolution, PP attachment resolution, and word ambiguity resolution. These improvements allow the chatbot to provide more accurate and contextually appropriate responses to user input.

Second, the enhanced chatbot incorporates personalization by asking for and remembering the user's name. This feature helps build rapport between the chatbot and the user, leading to a more engaging and satisfying user experience.

Third, the enhanced chatbot is capable of learning from its interactions by updating its knowledge base. This adaptability allows the chatbot to continually improve its performance and better cater to the needs of individual users.

Finally, the enhanced chatbot maintains a chat history, which can be valuable for analyzing user behavior and improving the chatbot's performance. The chat history can also be saved for record-keeping purposes, providing an audit trail for organizations that require such documentation.

## 4.3. Future work and potential improvements

There are several areas for potential improvement and future work on the enhanced chatbot. Some possibilities include:

1. Further enhancing anaphoric resolution: The current implementation of anaphoric resolution could be improved to handle more complex cases and additional pronouns, such as "we", "you", and "they". More advanced techniques, like coreference resolution algorithms, could be employed to achieve better results [33].
2. Implementing semantic role labeling (SRL): SRL could be added to the chatbot's NLP capabilities to better understand the semantic relationships between words in user input [34]. This would allow the chatbot to extract more meaningful information from input and generate more contextually relevant responses.
3. Integrating external knowledge sources: The chatbot's knowledge base could be expanded by incorporating external sources of information, such as online databases or APIs, to provide more accurate and up-to-date responses [35].
4. Sentiment analysis: The chatbot could be enhanced with sentiment analysis capabilities to recognize and respond to the user's emotions [36]. This would allow the chatbot to provide more empathetic and personalized responses, improving the user experience.
5. Multi-turn conversation support: The current chatbot could be improved to better handle multi-turn conversations, allowing it to engage in more complex and meaningful interactions with users [37].
6. Evaluation metrics: Developing evaluation metrics to assess the performance of the chatbot and its NLP enhancements would be valuable for measuring improvements and guiding future development [38].

In conclusion, the enhanced chatbot presented in this report demonstrates a variety of NLP techniques that can be used to improve its understanding of natural language and provide more accurate and contextually appropriate responses. By implementing these enhancements, the chatbot can better cater to the needs of individual users and engage in more meaningful interactions. Future work can focus on further improving the chatbot's NLP capabilities and exploring additional techniques to enhance its performance and user experience.

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