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LUCRARE DE DIPLOMĂ

Agent conversațional pentru
interacțiunea cu personalități istorice

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Bachelor Thesis

Conversational Agent for Interacting with Historical Figures

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Abstract

This paper describes a conversational agent that answers questions pertaining to a given historical figure. The answers are selected from a set of sentences extracted from the biographical text of that personality using syntactic and semantic analysis on both the question and the sentences at hand. This is accomplished with a top-down approach, starting from the entire biographical text and working our way down, in several steps, to the

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Chapter 1

Introduction

More than 60 years ago, Alan Turing raised the question "Can machines think?" [1].
Can people believe that a machine thinks?

Chapter 2

Project Overview

2.1 Project Motivation

2.2 Project Objective

2.3 Project Description

Chapter 3

Related Work

The following sections in this chapter present the background in the areas of NLP, question answering,

3.1 Open Domain Question Answering

* IBM Watson

3.2 Conversational Agents

* Freudbot

Chapter 4

Tools

The next sections present the most important programming tools used to build the conversational agent. The first two sections describe tools that are part of the ontological approach to the implementation of the program.

4.1 DBpedia

DBpedia¹ is a project that aims to convert content extracted from Wikipedia into a structured dataset, that is subsequently made available on the World Wide Web. The final purpose of this project is to provide an interface so that the users can query Wikipedia in a structured manner using Semantic Web techniques. The structured information is published using the RDF² specifications. In addition, DBpedia links its dataset with other published open datasets, in total reaching 2 billion RDF triples (in 2007) [2].

The DBpedia datasets can be accessed in three ways:

- through the Linked Data interface, where the DBpedia resources (published as RDF data) can be accessed using URIs.
- using the SPARQL Endpoint that supports specific SPARQL queries.
- downloading RDF dumps containing larger parts of the DBpedia dataset.

The important aspect of DBpedia for building our conversational agent is that DBpedia has a separate, independent *Persons* dataset that has more than half a million RDF triples containing information (extracted from Wikipedia articles written in English) for around 760,000 people, as of 2012 [3].

¹DBpedia, dbpedia.org

²Resource Description Framework, <http://www.w3.org/RDF/>

4.2 ChatScript

ChatScript¹ is an engine for building conversational agents. ChatScript is a rule-based system relying on its own scripting language (similar to AIML²) to model the conversational behavior of an agent. Its purpose is to "pattern-match on general meaning" by using "sets of words and canonical representation." [4]

A chat-bot is modeled through a set of script files that contain rules. A rule is formed from a pattern and a response. The response represents the output that a ChatScript bot will provide if the input matches the pattern. Two ChatScript rules are presented in Listing 4.1. The elements in the parentheses constitute the pattern and the sentence after the pattern represents the answer returned if the user input matches the pattern. The * (star) symbol is a wildcard that can match none, one or more words.

```
u: ( Where * you * born ) In the capital .  
u: ( When * born ) This century .
```

Listing 4.1: ChatScript rules example

4.3 WordNet

WordNet³ is an online lexical reference database [5, 6] containing: words, lexical relations and semantic relations.

Word. A word is defined as a pair (f, m) between a form f (the string representation of the word) and a meaning m . If a word has more than one meaning (it is polysemous), WordNet differentiates between the meanings and keeps a pair (f, m) for each meaning. The polysemy of a word can be extended to its part of speech, i.e. a word can have different meanings depending on its part of speech; e.g. *die* can be a polysemous noun meaning either *dice* or is "a device used for shaping metal", or a verb meaning *decease*. In the WordNet database only "open-class words" are present. The database includes about 155,000 nouns, verbs, adverbs and adjectives [7].

Synonym set. The words are grouped into synonym sets, also known as *synsets*, which are the core element in WordNet. A synset is used to represent the meaning (or sense) of a word [6].

Lexical relations. A lexical relation between two words is a relation between the form of the words. For example, synonymy and antonymy is stored in the database as a lexical relation [5].

Semantic relations. A semantic relation is a relation between word meanings and is stored in the WordNet database as a pointer between synsets. The semantic rela-

¹ChatScript, <http://chatscript.sourceforge.net/>

²AIML: Artificial Intelligence Markup Language, <http://www.alicebot.org/aiml.html>

³Princeton University "About WordNet." WordNet. Princeton University. 2010., <http://wordnet.princeton.edu>

tions between the synsets are useful to model concepts like: hyponymy, hypernymy, meronymy etc.

4.3.1 MIT Java WordNet Interface

The Java WordNet Interface (JWI) is an Application Programming Interface (API) written for the Java programming language that is used to access and query the WordNet database files. JWI features calls to retrieve index words and synsets and calls that allow following lexical and semantic pointers [8]. Mainly, it can be used to access synonyms, antonyms and hypernyms/hyponyms of a given word. Three most important advantages to use JWI as presented in [9] are:

- JWI provides both file-based and in-memory dictionary implementations, allowing you to trade off speed and memory consumption
- JWI sets no limit on the number of dictionaries that may be instantiated in each JVM
- JWI is high-performance, with top-ranked speeds on various retrieval metrics and in-memory dictionary load time

It can be seen in the benchmarks from [9] that JWI is one of the fastest libraries for WordNet. Average access time for retrieval of an entry and for iterating through entries in the database are shown in Table 4.1.

Object	Retrieval time (μ s)	Iteration time (μ s)
Index Word	12.3	296
Synset	7.1	798
Word-by-Sense-Key	17.2	141
Exception Entry	16.1	4
Synsets by Index Word	-	1.8s

Table 4.1: Average time of access of WordNet database

4.4 Apache Lucene

Apache Lucene¹ is a text-search library written in Java. It provides an API for performing common search tasks like text indexing, querying, highlighting results and others [10]. Lucene achieves high performance due to the inverted index [11] approach. In addition, the search speed can be increased by placing the text in memory, using the RAMDirectory class.

Lucene’s three main features, presented below, are: analysis of incoming content and queries, indexing and storage and searching [10].

¹Apache Lucene Core, <https://lucene.apache.org/core/>

Language Analysis. The texts to be searched and the queries are stored internally in a modified form for faster access. The transformations made are: character filtering, tokenization, stemming, lemmatization, stopwords removal and others.

Indexing and storage. Lucene supports inverted indexes on more than one field per document, useful for annotating the text with different information (e.g. ISBN). All this data can be stored on a persistent device (for large sets of documents) or, as previously stated, in the RAM memory for faster access (for reduced size documents). In addition, Lucene can be configured to use different kinds of query scoring, based on total word frequency, unique word count and total document frequency of all words [10].

Searching. The implementation of Lucene's querying supports several types of searching mechanisms, like: wildcards, fuzzy search, proximity search, binary operators and others [10]. Querying can be optimized by providing a number of top matches after which the search stops.

4.5 Stanford CoreNLP

Stanford CoreNLP is one of the most exhaustive tools for natural language analysis. It is an open source project written in Java and has a comprehensive API that is easy to use. Architecturally, Stanford CoreNLP is a pipeline that annotates the input text with relevant information, like the part of speech of the words. It also generates graph-like structures containing links between words, representing relations like: syntactic dependencies and co-references. The execution flow of the annotator is represented in Figure 4.1.

The provided annotators that can be included in the processing are: "tokenize", "cleanxml", "ssplit", "truecase", "pos", "lemma", "gender", "ner", "regexner", "parse", "sentiment" and "dcoref". Most of the annotators are built as separate modules that are integrated afterwards in the core. Some of these main modules are presented in the following sections.

4.5.1 Stanford Tokenizer

Although the tokenizer is not an independent part of the Stanford NLP project, it appears in multiple modules of the project. The role of the tokenizer is to split the raw text into a sequence of individual tokens [12]. The tokenizer uses Penn Treebank style tokenization¹. The functionality of the tokenizer is implemented in the *PTBTokenizer* Java class.

During the tokenization process, besides the actual list of tokens, the *PTBTokenizer* also generates a text annotation for each token in order to retrieve the original form of the text when needed. This is mostly useful when the lemmatization process, described below, is applied to the text.

¹Penn Treebank Tokenization Specifications, <https://www.cis.upenn.edu/~treebank/tokenization.html>

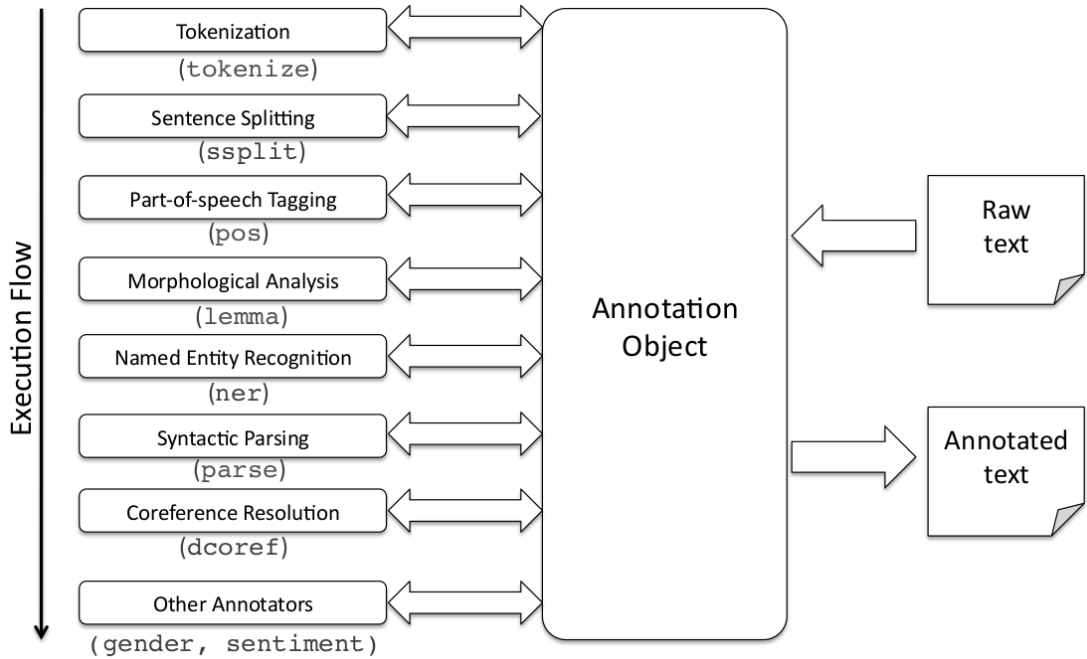


Figure 4.1: Stanford CoreNLP execution pipeline [12]

Another use for the tokenizer is to accomplish sentence splitting (added with the "ssplit" annotator option as mentioned before). This is done by tokenization after one of the sentence-ending characters (., ! and ?) if they are not grouped with other characters into a token (such as for an abbreviation or number) [13].

After the tokenization has been performed, the individual words can be lemmatized (using the "lemma" annotator option), meaning that a word is annotated with its dictionary form (or base form). For example: *has*, *had* and *having* become *have*; *children*, *child's* and *children's* become *child*.

4.5.2 Stanford Log-linear Part-Of-Speech Tagger

The purpose of the Part-Of-Speech (POS) tagger is to label words with their corresponding POS tag, using a maximum entropy POS tagger [12]. The English POS tagger uses the Penn Treebank tagset described in [14]. This type of tagging is particularly useful for syntactic analysis in NLP applications, for example it is important to determine a word's part of speech when finding the appropriate synonym for the word if the word is polysemous.

The POS tagger uses a cyclic dependency network model trained using lexical features of words extracted from the Penn Treebank dataset. The network is then used as a classifier fed with the given text as input. The architecture of the dependency network used for feature-rich POS tagging is described in depth in [15].

4.5.3 Stanford Named Entity Recognizer

The Stanford Named Entity Recognizer (NER) is an annotation tool that labels words (or sequence of words) that are likely to stand for names of things (like people and places). Stanford NER uses a statistical model trained on a collection of Reuters articles annotated with four entity types: person (PER), location (LOC), organization (ORG), and miscellaneous (MISC) [16]. The Stanford NER dataset contains statically assigned types for a set of entities, but it can also infer the type from the context, as seen in Table 4.2. Table 4.2 shows that *Bucharest* is a known entity with its type previously assigned as opposed to *Ploiești* which is wrongly considered a person in the sentence "*I like Ploiești*". Despite this fact, the NER successfully identifies *Ploiești* as a location in the "*I live in Ploiești*" sentence.

Stanford NER is useful for the Stanford Co-Reference System, described in subsection 4.5.4, where a relation needs to be established between a pronoun (her, his, it etc.) and a name of a person.

Sentence	Token	NER
<i>I like Bucharest</i>	Bucharest	Location
<i>I live in Bucharest</i>	Bucharest	Location
<i>I like Ploiești</i>	Ploiești	Person
<i>I live in Ploiești</i>	Ploiești	Location

Table 4.2: Inference of types using the Named Entity Recognizer

4.5.4 Stanford Deterministic Coreference Resolution System

Stanford's Coreference Resolution System implements mention detection and both pronominal and nominal co-reference resolution [12]. This tool is used to link pronouns to the entities they refer to. In order to achieve that, the architecture of the system applies several deterministic co-reference models, one after the other. The first, and most important step of this algorithm is the *mention detection*, where the nominal and pronominal mentions are identified using an algorithm that selects all noun phrases, pronouns and named entity mentions. After that, the co-reference models are applied from highest to lowest precision. All the steps of the algorithm are described in [17].

An example of this system's functionality is presented in Figure 4.2, where the pronoun *he* is linked to the word *Lennon*, the name of the person the pronoun refers to.

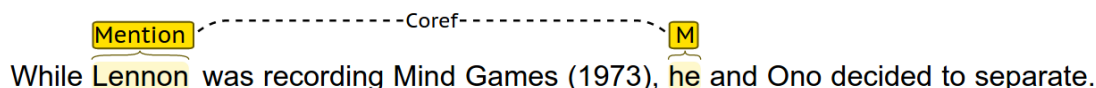


Figure 4.2: A co-reference example where the mention of the pronoun *he* is connected by the *coref*-type relation with the mention of the entity *Lennon*

Chapter 5

Implementation

The architecture of the application contains two main modules: the user interface (UI) in the form of a Web Application, presented in section 5.1 and the actual implementation of the conversational agent, detailed in section 5.2.

In the next sections reference to the chat client, chat server and chat-bot signify the front end user interface, the back end of the web application and the conversational agent program respectively.

5.1 Web Application

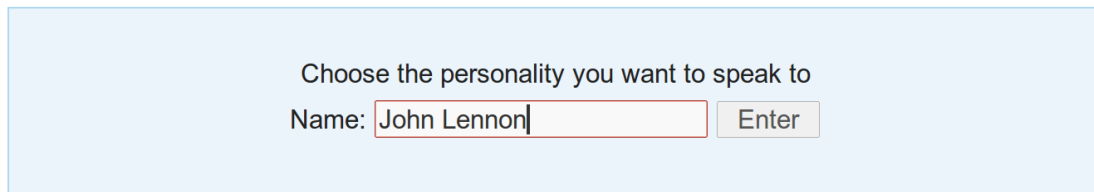
The web application is the interface with the help of which the user interacts with the conversational agent. It implements a chat client, a program where the user can input its questions and see the answers processed by the conversational agent and returned by the chat server. It also implements a chat server that connects to the chat-bot's endpoint. After the connection succeeds, the chat server passes the query received from the client to the chat-bot, waits for a reply and then sends the reply back to the client.

The chat client is described in subsection 5.1.1 and the chat server is described in subsection 5.1.2. The chat-bot's endpoint of the aforementioned connection between him and the chat server is explained at large in section 5.2.

5.1.1 Front End

The front end is written in HTML, CSS and JavaScript and it is composed of two main screens: the first page where the user can input the name of the personality he wishes to speak to; the second page, the actual chat box, where the conversation is displayed, and the input box, where the user can write the question and submit it.

The first screen is shown in Figure 5.1. Clicking the *Enter* button would send a request to the chat server that would later on initialize the chat-bot with the inputted personality.

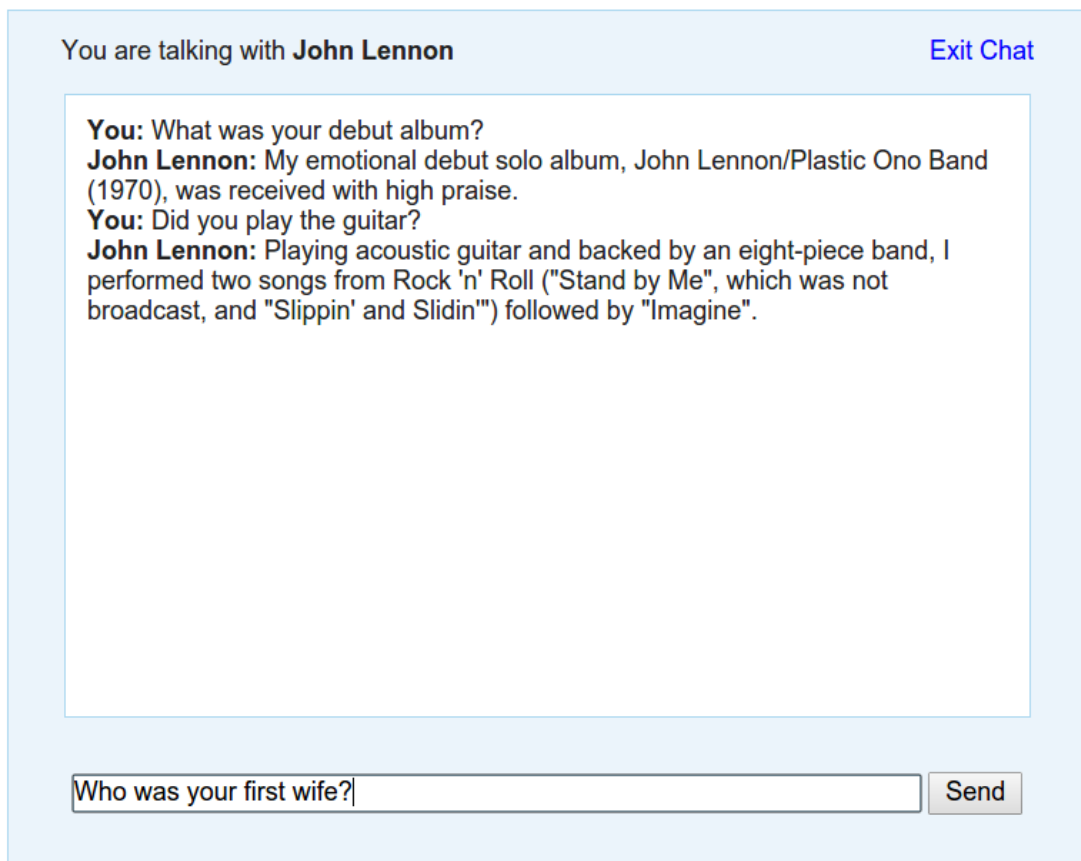


Choose the personality you want to speak to

Name:

Figure 5.1: The first page of the Web App where the user can input the name of the personality he wants to talk with

In Figure 5.2, the chat box containing a few questions and answers can be seen. At the bottom of the chat box there is the input text box where the user can write its questions and submit them.



You are talking with **John Lennon** [Exit Chat](#)

You: What was your debut album?
John Lennon: My emotional debut solo album, John Lennon/Plastic Ono Band (1970), was received with high praise.
You: Did you play the guitar?
John Lennon: Playing acoustic guitar and backed by an eight-piece band, I performed two songs from Rock 'n' Roll ("Stand by Me", which was not broadcast, and "Slippin' and Slidin'") followed by "Imagine".

Figure 5.2: The page where the user can submit questions and see the replies

The conversation is saved on the client-side, in memory, using JavaScript, and is persistent until the page is refreshed or closed.

The questions are submitted by sending a synchronous HTTP GET request to the server. The request contains the question. The request is sent using AJAX (Asynchronous JavaScript + XML) and contains a random generated number in the URL so that the browser doesn't serve a cached page. For example, `http://<hostname>/chatbot.`

php?question=What+was+your+debut+album%3F&t=0.023473239736631513 sends the question *"What was your debut album?"* to the chat server.

5.1.2 Back End

The server side of the web application is made up of XAMPP^{1,2} and the PHP scripts that implement the connection with the chat-bot.

Functionally, the communication is accomplished by using a local socket to socket connection between the web server and the conversational agent server. A snippet of the code that shows the principles of communication between the two servers is presented in Listing 5.1. The main aspects of the program are highlighted through comments in the code. The flow of the communication is shown in Figure 5.3.

```
1  /* Establish connection */
2      $sock = socket_create(AF_INET, SOCK_STREAM, SOL_TCP)
3          ;
4      if ($sock == FALSE) {
5          echo "error creating socket";
6          exit("error");
7      }
8      $result = socket_connect($sock, $address, $port);
9      if ($result == FALSE) {
10         echo "error connecting";
11         exit("error");
12     }
13
14     /* Send the question to the conversational agent */
15     $question = $_GET["question"] . "\n";
16
17     $err = socket_write($sock, $question, strlen(
18         $question));
19
20     /* Wait for the answer */
21     $answer = socket_read($sock, 12000);
22     echo "$answer";
23
24     socket_close($sock);
```

Listing 5.1: Socket communication between the web server and the chat-bot

¹XAMPP Website <https://www.apachefriends.org/index.html>

²XAMPP is a bundle containing the Apache HTTP server, a MySQL server and a PHP and Perl interpreter

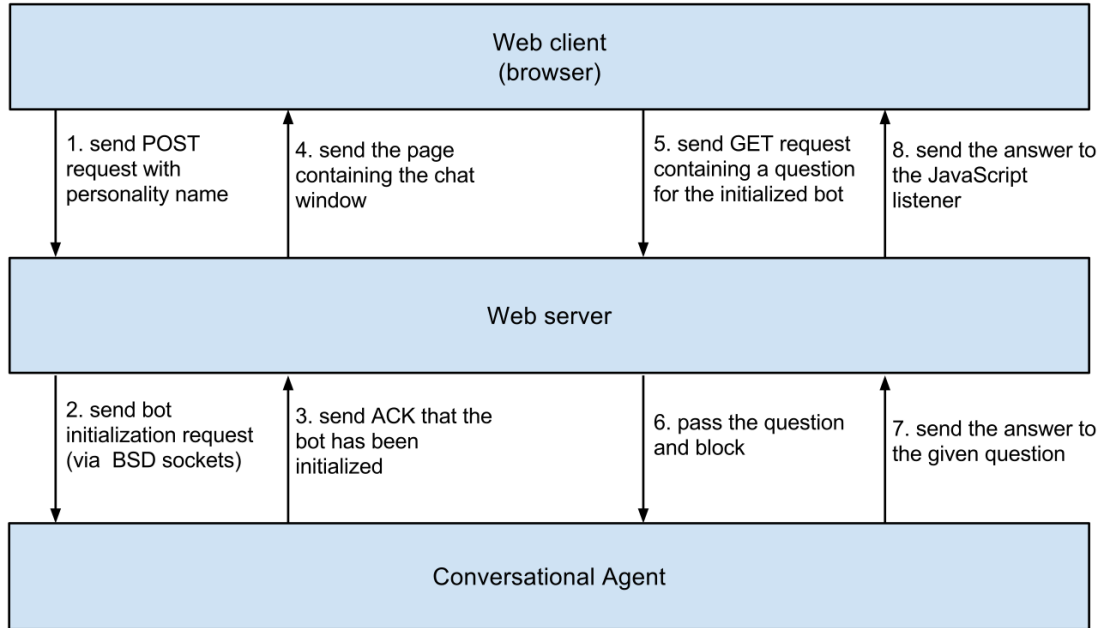


Figure 5.3: The communication flow between the client, web server and conversational agent server

5.2 Conversational Agent

This section contains the architectural decisions and the implementation details of the conversational agent. First, in subsection 5.2.1, the rule-based system approach using the DBpedia ontology and the ChatScript engine is described. Next, the approach to implementation employing the *answer sentence selection* method is presented.

5.2.1 Rule-based System Approach

Expressing a Property In order to understand what is trying to be expressed in a sentence, we start from the DBpedia properties of a large set of people. Subsequently, for every property, we try to determine how that property is expressed in the Wikipedia corpus. For the information extraction, we use Stanford CoreNLP. To find the manner in which a property is expressed, we searched the value of that property in the sentences from Wikipedia where the person which the article is about appears in. Having the desired sentence identified, we annotated it using Stanford CoreNLP and obtained a syntactic parse tree. Analyzing this tree, we determined that the root is the verb directly connected with the subject. Having the parse tree, we considered that the best way to express the property is the path from that property to the root verb. Applying this algorithm to a large set of people, we managed to build a big, but extensible knowledge base by introducing the most relevant output expressions in a knowledge base.

Pattern Generation In order to generate ChatScript files for a specific person, we fetch that person's Wikipedia page, split it into phrases and keep only those that have the

person as a subject. This filtering was done using the Stanford Deterministic Co-reference Resolution System. After extracting all the phrases referring to the current historical figure, we select only those that express a property from DBpedia matching the expression against the knowledge base. We then create a rule-answer entry to add to the ChatScript files. The rule is represented as an expression of a property that appears both in the analyzed sentence and the knowledge base. The answer is the analyzed sentence from Wikipedia which is converted to be expressed in the first person. The conversion from the third person to the first person of the sentence is accomplished with Stanford’s Part-of-Speech Tagger and CoreNLP. All these patterns are written in ChatScript’s file hierarchy. For a fast and easier way to find the answer, we arranged ChatScript’s files by the properties of the person.

5.2.2 Answer Sentence Selection Approach

Because it is impossible to build an exhaustive rule-based system, a secondary approach to this problem has to be taken into consideration in order to give a good answer. In addition, ChatScript has its own limitations coming from the fact that it ignores a rule after it first matches it. Therefore a fallback option is needed in case the former approach fails to provide an answer. Considering the fact that the former approach gives better answers the simpler and more common questions are asked, we observe that either it fails to match questions that are more complex or it has too many matches for a question that uses a common verb (like “to be” or “to have”) and the results will be inaccurate or noisy. The solution to avoid this is to try and find the answer directly from the source of the previously described knowledge base with an ad hoc approach considering every sentence from that respective source.

Following the goal of having to answer a question for a certain historical figure, the set of possible answers is reduced to a set of sentences from that person’s biography. This leaves us with the task of identifying a sentence from a biography that has the highest probability of correctly answering the question at hand. Considering what was previously stated, that this approach tries to find the answer to a more complex question, we can assume, at least for now, that there is a great deal of semantic information embedded in the form of the question (lexically and semantically) so that the chances are a part of the answer textually lies in the question. Therefore, what we can do is actually search for the question (or paraphrases of the initial question) in the reference text.

The design of this approach is built with three main goals in mind: performance regarding speed, small memory footprint and high answer accuracy.

Speed. Good speed efficiency is achieved by using a pipeline architecture, where the set of potentially correct answers is iteratively reduced as the methods for sentence selection increase in complexity. This pipeline can be viewed as a series of sieves that sequentially filter the set of input sentences. The pipeline architecture is discussed in depth in subsection 5.2.2.1. In addition, the use of Lucene’s in-RAM storage (described in section 4.4) saves a lot of time from accessing persistent storage devices (HDD, SSD etc.). More than that, all tools used are highly optimized and no extra features of these tools are integrated in the program if not necessary.

Memory. By not using a rule-based system, there is no need for huge databases stored on the hard-drive. Also, if the program has internet access, the pages needed for information retrieval can be fetched immediately from the Web. Although, if this is not possible, the biographical corpus used by the agent can be scaled according to the desired set of people the program could potentially instantiate. Regarding the RAM memory, the efforts to minimize the memory footprint are backed by:

- the optimized indexing of Apache Lucene
- the control of Stanford CoreNLP annotations
- the Java language references support (by not duplicating paragraphs or sentences)
- using hard-drive stored dictionaries for WordNet

Answer accuracy. The "correctness" of the answers is achieved through the scoring method of the selected sentences, using both Lucene's internal scoring system and own formulas for scoring sentences according to the score of the paragraphs and WordNet's frequency count for the synonyms considered in the alternative formulations of the input question.

The class diagrams for the program can be seen in Appendix A.

5.2.2.1 Pipeline

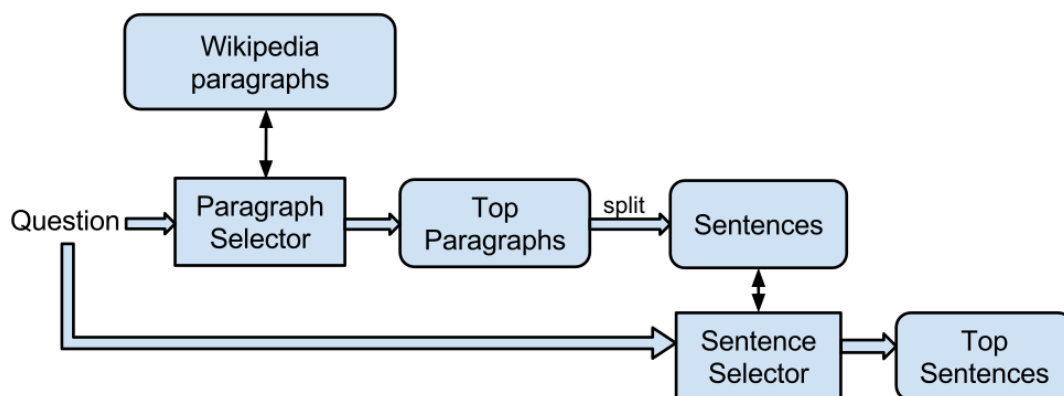


Figure 5.4: The lexical filtering part of the pipeline

Answer sentence selection

To get the best results out of this approach, we need to follow a number of steps. First, we need to remove unnecessary words, including stop words, the interrogative words (what, when, where, who, why and how) and irrelevant verbs ("to be", "to have" and other similar verbs as described above) in order to remain only with meaningful words, i.e. the kernel of the question. Second, we want to use the Stanford CoreNLP software to lemmatize the question (i.e. to convert every word to its appropriate canonical form) because, as described later on, the corpus used for a historical figure will be lemmatized too. This will help in the search step because words will more likely match if they

are in their base form. Third, we try to find alternative ways of expressing the input question and attempt to search for all this variants in the biographical text. We do this by trying different synonyms for the words in the question so that we can get more results, even if the initial question is formulated in such a way that it does not contain the exact words that might appear in the sentence representing the correct answer. Next, the top paragraphs from the Wikipedia article are filtered based on the textual matching score between the question and the respective paragraph given by Apache Lucene [1], a text search tool. Then, we apply the same algorithm at the level of sentences instead of paragraphs. In short, to get the best answer the corpus is divided in separate paragraphs and a small set of paragraphs where the answer sentence might be part of are selected. Next, we attempt to find an even smaller set, made of sentences that are the best candidates to answer the question. After we have a set of sentences that passed the lexical filtering, we want to eliminate those in which the subject of the sentence does not match the subject of the question. These mechanism is similar to maintaining the semantic relations as described in [5], and presented above in the Related Work section. To achieve that, we want to use Stanford CoreNLP, and in particular the Stanford Deterministic Co-reference Resolution System, to determine who is the subject of a given sentence. After the syntactic filtering we are left only with the semantic filtering. This means we want to filter out all the sentences that do not have the type as the one expected by the question. For example, questions starting with “When” expect a answer sentence that contains a numerical value. Finally, we choose the first sentence in order of the previously gathered relevance scores. Using the aforementioned approach we manage to answer more complex questions.

5.3 Testing

Chapter 6

Results

Chapter 7

Conclusions and Future Work

7.1 Summary

7.2 Future Work

Appendix A

Class Diagrams

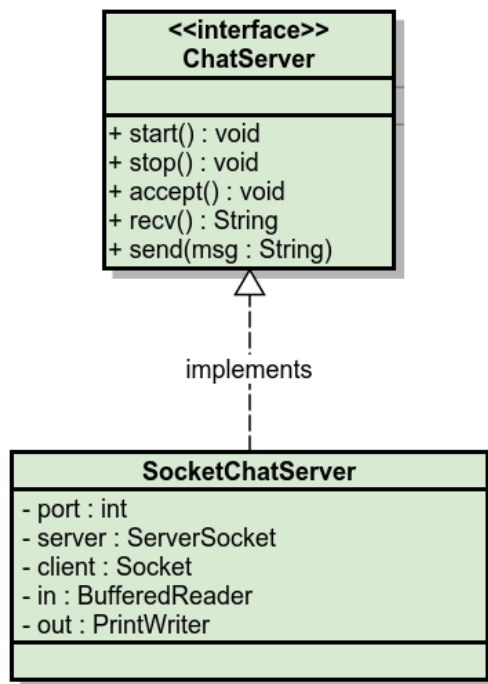


Figure A.1: Class diagram for the chat-bot server

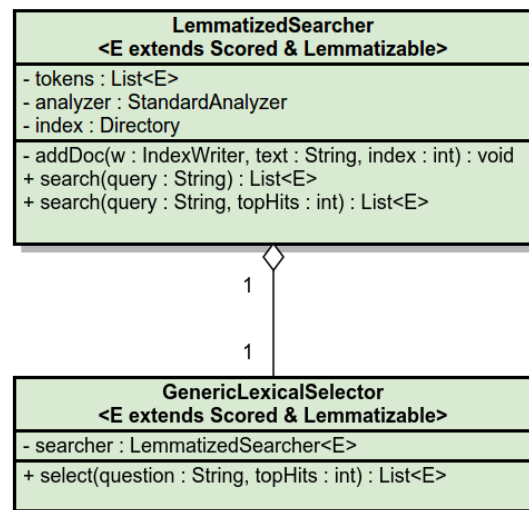


Figure A.2: Class diagram for the text searcher

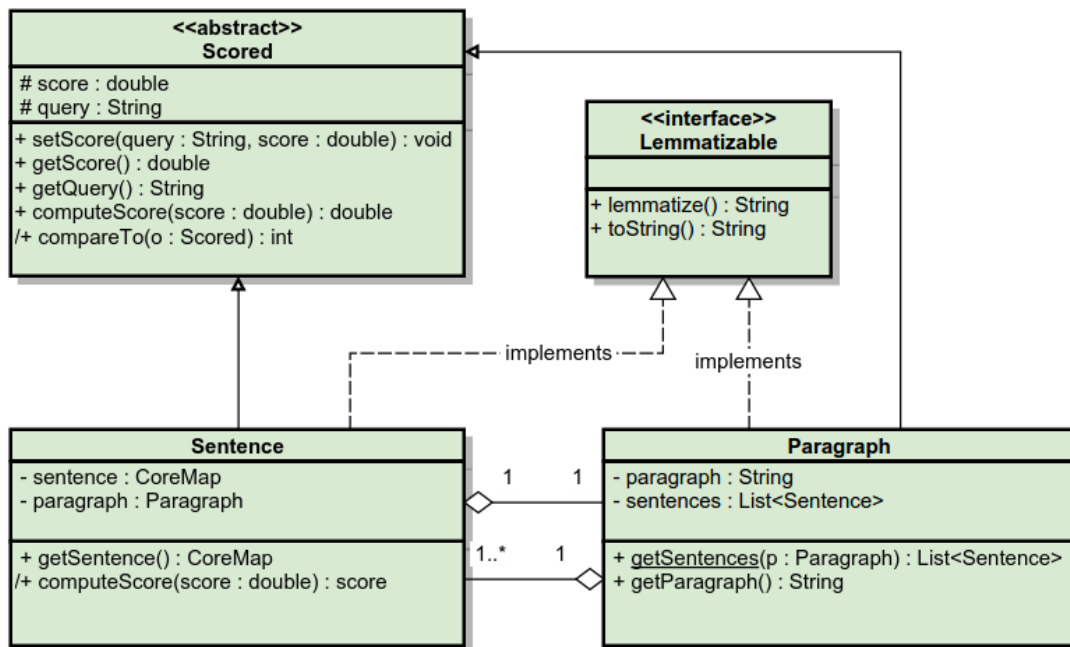


Figure A.3: Class diagram for the objects (paragraph, sentence) being manipulated

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