NATURAL LANGUAGE INTERFACE TO RELATIONAL DATABASE:

A SIMPLIFIED CUSTOMIZATION APPROACH

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Plagiarism Declaration

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Abstract

Natural language interfaces to databases (NLIDB) allow end-users with no knowledge of a formal language like SQL to query databases. One of the main open problems currently investigated is the development of NLIDB systems that are easily portable across several domains. The present study focuses on the development and evaluation of methods allowing to simplify customization of NLIDB targeting relational databases without sacrificing coverage and accuracy. This goal is approached by the introduction of two authoring frameworks that aim to reduce the workload required to port a NLIDB to a new domain. The first authoring approach is called top-down; it assumes the existence of a corpus of unannotated natural language sample questions used to pre-harvest key lexical terms to simplify customization. The top-down approach further reduces the configuration workload by auto-including the semantics for negative form of verbs, comparative and superlative forms of adjectives in the configuration model. The second authoring approach introduced is bottom-up; it explores the possibility of building a configuration model with no manual customization using the information from the database schema and an off-the-shelf dictionary. The evaluation of the prototype system with geo-query, a benchmark query corpus, has shown that the top-down approach significantly reduces the customization workload: 93% of the entries defining the meaning of verbs and adjectives which represents the hard work has been automatically generated by the system; only 26 straightforward mappings and 3 manual definitions of meaning were required for customization. The top-down approach answered correctly 74.5 % of the questions. The bottom-up approach, however, has correctly answered only 1/3 of the questions due to insufficient lexicon and missing semantics. The use of an external lexicon did not improve the system's accuracy. The bottom-up model has nevertheless correctly answered 3/4 of the 105 simple retrieval questions in the query corpus not requiring nesting. Therefore, the bottom-up approach can be useful to build an initial lightweight configuration model that can be incrementally refined by using the failed queries to train a top-down model for example. The experimental results for top-down suggest that it is indeed possible to construct a portable NLIDB that reduces the configuration effort while maintaining a decent coverage and accuracy.

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Table of contents

List of tables

List of figures

Code listings

Chapter 1 Introduction

Spoken natural languages are used by humans to verbally communicate with each other. Japanese, English, French and Chinese are examples of natural languages. Natural languages contrast with artificial languages which are constructed by humans; examples of artificial languages include programming language and database query languages. The field of computer science interested in analysing natural language is called Natural Language Processing (NLP).

Tamrakar & Dubey (2011) define Natural Language Processing as a "theoretically motivated range of computational techniques for analysing and representing naturally occurring texts at one or more levels of linguistic analysis for the purpose of achieving human-like language processing for a range of tasks or applications". NLPs' objective is to perform language processing. The NLP field in the early days targeted to achieve Natural Language Understanding (NLU), but this goal has not been achieved yet (Kumar, 2011) and current works focus toward developing efficient theories and techniques for natural language processing. NLP research focuses on particular applications with narrowed purposes; this include among others:

- Information retrieval (IR) aims to mine for an interesting piece of information from large corpus of text;
- Machine translation (MT) aims to achieve automatic language translation;
- Natural Language Interfaces (NLI) aim to develop human-computer interfaces enabling users to interact with the computer through natural languages.

NLP borrows a lot from computational linguistics; as it studies languages from a computational perspective (Kumar, 2011). Natural Language Interfaces constitute a subfield of NLP, aiming to simplify human-computer interactions by enabling computers to process commands and produce results in natural language. Natural Language Interfaces to databases (NLIDB) is the most popular sub-domain of NLI.

Natural Language Generation (NLG) is also a sub-domain of NLI focusing on automatic generation of natural language. A NLG module can be included in a NLI to allow the system to produce results in natural language.

1.1 Natural language interfaces to databases

Information plays a crucial role more than ever in our nowadays organizations (Sujatha, 2012). The Internet is growing at a fast rate, creating a society with a higher demand for information storage and access (Range et al, 2002). Databases are the de facto tool to store, manage and retrieve large amount of data. Unsurprisingly, they are used in various application areas in multiple organizations (Nihalani et al, 2011). Databases use a formal query language to communicate; currently, Structured Query Language (SQL) is the norm and standard way to interact with relational databases, but it is difficult for non-domain experts to learn and master. Graphical interfaces and form-based interfaces improve data analysis (Calvanese et al, 2010) and are easier than formal languages but still constitute artificial languages that require some training to be properly used by casual users (Panja & Reddy, 2007). One of the most convenient means for casual users to ask questions to databases is to use natural language they are accustomed to (Freitas & Curry, 2014).

Research in Natural Language Interface to Databases aims to develop intelligent and easy to use database interfaces by adopting the end user's communication language (Sujatha, 2012). A NLIDB is "a system that allows the user to access information stored in a database by typing requests expressed in some natural language" (Androutsopoulos et al, 1995). NLIDB systems receive users' inputs in natural language (text or speech) and translate them into commands in a formal language (like SQL or MDX, for DataWarehouse) that can be processed by a computer. This approach greatly simplifies the interaction between the system and user, since there is no need to learn and master a formal query language (Sharma et al, 2011).

1.2 Problem statement and motivation

Full understanding of natural language is a complex problem in artificial intelligence that is not completely solved yet. There are still a lot of challenges that need to be addressed before developing a fully usable natural language interface that can accept arbitrary natural language constructions. The main open problems include system portability, disambiguation, and management of user expectation. This research addresses the first problem.

Natural language interfaces often require tedious configuration to be ported to new domains. The early works on NLIDB have been tailored to interface a particular knowledge domain or application; examples include LUNAR (Woods et al, 1972) and LADDER (Hendrix & Sacerdoti, 1978). The natural language processing literature contains several works aiming to build highly portable NLIDB with various levels of success. However, a review of the literature reveals a trade-off between portability and coverage. Highly portable systems tend to have a limited coverage while systems achieving high accuracy tend to be hard to customize and maintain. This research addresses the problem of bridging the gap between portability and coverage while avoiding the loss of accuracy.

1.3 Research questions

This research addresses the challenge of simplifying customization of NLIDB without negatively impacting the linguistic coverage and accuracy of the system. The study hypothesizes the feasibility of a portable NLIDB design targeting a relational database whose configuration requires only the knowledge of database and the subject domain without sacrificing the system coverage and accuracy. The following research questions are investigated:

- Is the exploitation of an unannotated corpus of sample questions combined with automatic generation of configuration for negative form of verbs, comparative and superlative form of adjective an effective approach to reduce the workload required to customize a NLIDB targeting relational databases?
- Is it viable to use the database schema and an off-the-shelf dictionary as the only source of configuration data for an authoring system requiring no manual customization?

1.4 Scope

The NLIDB design in this research work will use SQL as the formal language to query relational databases. Additionally, the system will support only English natural language questions that are assumed to be free of spelling or grammar errors. And finally, the parser engine is based on symbolic approach as the parsing method of natural language questions. This research will explore two authoring approaches aiming to reduce the workload needed to customize a NLIDB system. The first approach is called *top-down*, it assumes the existence of a list of sample questions before customization. The sample query corpus is used to harvest key lexical terms and construct a

customization framework based on mapping harvested elements to either database objects or their corresponding semantics. The second customization method is called *bottom-up*, it explores the feasibility of porting a NLIDB to a new database without any manual customization, using only the database schema and WordNet (a public external dictionary) as source of configuration information.

1.5 Methodology

The present research project is based on the computer science experimental methodology which consists of identifying "concepts that facilitate solutions to a problem and then evaluate the solutions through construction of prototype systems"(Dodig-Crnkovic, 2002). In this research, we propose a design and evaluation of an experimental prototype called NALI which aims to simplify NLIDB customization. The experimental research has been completed in two main phases which are the prototype design and its evaluation. The waterfall model has been used to implement the prototype. The development cycle went through the following five phases: requirement gathering, design, development, testing, and evaluation.

A system based evaluation method, i.e., an intrinsic evaluation, has been selected to evaluate the experimental prototype. This choice is firstly motivated by the fact this research aims to contribute mostly on improving the efficiency and performance of NLIDB customization. System based evaluations allow assessing quantitatively the system's performance in controlled environments while user based or extrinsic evaluations are better suited to assessment of qualitative features like user perception of the system (Woodley, 2008). A system evaluation will secondly allow easily comparing the result with similar systems that are mostly evaluated through a system based approach as well.

The prototype was evaluated with geo-query[1], a corpus of sample questions, and its related database (Tang & Mooney, 2001). We built a gold SQL result in order to automate the evaluation of the correctness of the responses returned by the system. The metrics[2] used to evaluate and compare the system performance are precision and recall.

The tests were run in a computer with the configuration below:

- Hardware configuration: processor Intel(R) Core(TM) i7-2630QM CPU @ 2.00 GHz with 16 GB of RAM;
- Software configuration: Windows 7 Professional, PostgreSQL 9.4, Java version 1.7.

The experimental results are recorded in several html files that are kept in folders labelled with the date and time of the experiment. The configuration data used for evaluation were recorded in a file and can be used to re-run the experiments.

1.6 Overview of the thesis

The remainder of this thesis is structured as follows:

Chapter 2 gives some context and background on natural language processing and natural language interface to databases. The related work section focuses on research aiming to simplify the task of customization and the chapter concludes with a synthesis of the current state of the art and open problems.

[1] The motivations for choosing geo-query are presented in section 5.1.
[2] The definitions for precision and recall are presented in section 5.1.

Chapter 3 presents the design of top-down and bottom-up approaches and describes the data structures and algorithms used for both methods.

Chapter 4 presents the design of the processing pipeline for NALI and describes each of the main phases of query processing, namely lexical analysis, syntactic analysis, semantic analysis and SQL translation.

Chapter 5 describes the material and design of experiments used to evaluate the methods proposed in Chapter 3 and Chapter 4.

Chapter 6 presents the experiment results followed by a discussion and interpretation of the outcomes.

Chapter 7 concludes the thesis with a presentation of the main contributions and possible future work.

Chapter 2 Background

This chapter presents a context to NLIDB with a focus on the approaches toward easily customizable systems and the related work. The first section draws a bigger picture on approaches and techniques used by NLIDBs to process natural language inputs and concludes with a discussion on the problem of NLIDB portability. The second section looks closely at the approaches used in the literature to simplify NLIDB customization and reviews in depth the research projects whose objectives and approaches are similar to the present research. The chapter concludes with a summary of the related literature.

2.1 Natural Language Interface to Databases

NLIDBs allow non-technical users to query databases using natural language sentences. To achieve this, a NLIDB needs to process natural language input and produce a formal query like SQL to query a database. The next sections present the approaches used to process natural language, the levels of linguistic analysis, the main architectures of NLIDB and finally a discussion on portable NLIDBs.

2.1.1 Approaches to natural language processing

There are three main approaches to achieve natural language processing: symbolic, statistical and connectionist approach (Pazos et al., 2013). Symbolic and statistical approaches have been used in the early works in the NLP field, while connectionist approaches are relatively recent. Research conducted between 1950 and 1980 focused on development of symbolic theories and implementations. The symbolic approaches are based on in-depth analysis of linguistic properties and sentence grammatical structures. This analysis uses a set of well-formed rules predefined by a human expert. Statistical approaches are based on analysis of large text corpora to automatically develop an approximated general model of linguistic phenomena. There is no need, therefore, to manually create rules or world knowledge. Statistical approaches require large datasets of text corpora as their primary source of evidence. Statistical methods regained popularity in the 1980's, thanks to the broader availability of computational resources. Like in the statistical approaches, the connectionist approach develops generalized models from large text samples. Connectionism uses an artificial neural network (ANN) to model language features. The ANN is constituted of interconnected simple processing units called neurons. The knowledge is stored as weights associated to connections between nodes. Like in the statistical approaches, the connectionist approach develops generalized models from large text samples. We compiled in Table 1 a summary of the similarities and differences between approaches.

The symbolic approaches have the advantage of being simple to implement; however, their functionalities are limited by the quality and quantity of rules defined. Statistical and connectionist methods are more flexible and can learn through training; but this learning depends on the effectiveness of the training corpus (Pazos et al., 2013). Hybrid NLPs aim to complementarily use the strengths of all approaches to effectively address NLP problems. An example of a hybrid system can be found in (Mamede et al, 2012).

Table 1 – Comparison of approaches to natural language processing

	Symbolic approach	Statistical approach	Connectionist approach
Data collection	Prior data collection not compulsory	Requires large text corpora to build the model	
Model building	Performed manually by a linguistic expert	A statistical model is built from text corpora	A connectionist model is built from large text corpora
Rules	Manually defined beforehand	Rules built automatically from statistical models	Individual rules typically cannot be recognized, they are hidden in the neural network
Robustness	Fragile when presented with unusual, incomplete or ill-formed inputs	More robust than symbolic approach, provided that the training dataset is large enough	Robust and fault tolerant; deals efficiently with incomplete and noisy input (as the system knowledge is spread across the network)
Flexibility	Based on well formatted rules produced by human experts. Lack therefore flexibility, as the expert inputs are required for any adaptation	More flexible than symbolic, require a new dataset for training to adapt	Very flexible, can adapt by updating the link weights in real time, using examples provided
Suitable tasks	Can handle implementation of higher levels (discourse and pragmatic analysis). Suitable for tasks where linguistic phenomena are well known and steady (does not change often) like natural language interfaces	Suitable for task where linguistic phenomena are not well known and subject to frequent evolutions. Example: machine translation, information retrieval, etc. Can only deal with lower level analysis (morphological, lexical and semantic analysis)	

2.1.2 Phases of linguistic analysis

The processing of natural language can be achieved in several levels focusing on different aspects of language analysis. This paragraph gives a brief summary of each of these analysis levels.

Phonological analysis: phonology refers to the study of sounds and the way they are organized to produce spoken natural language (Marlett, 2001).

Morphological analysis: this level deals with the componential nature and structure of words. Words are composed of morphemes, which represent the smallest units of meaning. For instance, the word “interaction” is composed of three different morphemes: “inter” (the prefix), “act” (the root) and “ion” (the suffix). The meaning of morphemes is the same for all the words, making it possible to understand any given word by breaking it into its constituents (Aronoff & Fudeman, 2011).

Lexical analysis: also referred to as tokenization, is the process of breaking a stream of characters into meaningful unit elements (i.e. words) called tokens (Bird et al, 2009).

Syntax analysis: the syntax represents the structure of a language. For natural language, the syntax defines the order, connections, and relationships between words. The ensemble of syntax rules forms the language grammar (Nigel, 1987). Syntactic analysis, referred to sometimes as parsing is the process of analyzing a text structure to determine if it respects a given formal grammar. Context Free Grammars (CFG) is the most used grammar in syntactic analysis (Kumar, 2011).

Semantic analysis: this level deals with possible meanings of natural language inputs, by analyzing interactions in the word-level meanings within a sentence (Kumar, 2011). This level includes also disambiguation of words with several possible interpretations, in order to ideally keep only one final meaning for the sentence. A computational representation or knowledge representation is needed to model, store and process sentence meaning (Kumar, 2011). First Order Logic or another logic language can be used as a formal representation model to represent sentence meaning.

Discourse analysis: James Paul Gee (2005) defines discourse analysis as “the study of language-in-use”. At this level, the meaning of several sentences is analyzed to draw an overall sense, while semantic analysis focuses on the meaning of a single sentence.

Pragmatic analysis: at this level, external contextual knowledge is introduced to refine the discourse meaning (Kumar, 2011). For example, a mobile handset NLP being queried “What’s the weather like today ?” can use pragmatic analysis to “understand” that the current geographical position is needed to answer the query, and obtain it through GPS.

Currently, there are significantly more NLP systems implementing the four lower levels of analysis. This can be explained by the fact not all NLP actually need to analyze text at higher levels. In addition, lower levels have benefited from extensive research work. Lower level analysis is done by applying rules on small units: morphemes, words, and sentences. Higher levels, especially pragmatic analysis, often require extensive external world knowledge to perform efficiently.

2.1.3 Design and architecture of NLIDB

There are three approaches used to design NLIDB: pattern-matching, syntax-based systems, and semantic grammar systems.

Pattern-matching: systems were used in some of the early NLIDB. The input is matched with a set of predefined patterns. Only the questions defined in the patterns can be interpreted. Following is an example of pattern definition borrowed from (Androutsopoulos et al, 1995):

```
Pattern: ... "capital" ... <country>.

Action: Report Capital of row where Country = <country>.
```

This rule searches for the word "capital", followed by <country> which represents a word appearing in the list of countries in a database table. If this condition is matched, the system returns the content of column "Capital" where "Country" = <country>. This technique has the advantage that it

is simple: the rules are simple to write, no elaborate parsing module is needed, and as a result the system is easy to implement. One important disadvantage of a pattern-matching technique is that it can lead to a wrong answer when a query matches the wrong rule (Androutsopoulos et al, 1995).

Syntax-based systems: have a grammar that describes all the possible syntactic structures of queries (Androutsopoulos et al, 1995). The user's query is analyzed (parsed) syntactically and the resulting parsing tree is mapped to an intermediary language (see Fig 1), that will be translated into the database query language. LUNAR (Woods et al., 1972) is an early example of NLIDB using this approach. The parser can produce more than one parse tree for a given natural language; a syntax-based system needs in this case to resolve the ambiguity.

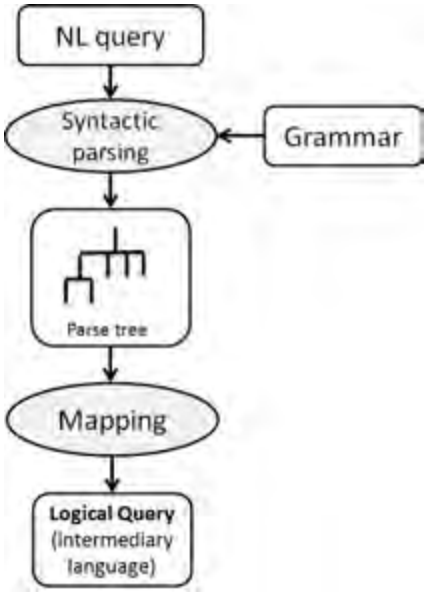


Fig 1 – Generic architecture of a syntactic parser

Semantic grammar systems: are similar to syntax-based systems in the sense that the input is also parsed to generate a parse tree. The difference lies in the fact that the leaf nodes represent semantic concepts instead of syntactic concepts. Semantic knowledge refers to the target domain and is hard-wired into the semantic grammar (Androutsopoulos et al, 1995). Semantic grammar is a standard approach used in several NLIDB implementations (Knowles, 1999). The query in natural language is parsed to generate a model or representation of the meaning of the sentence which will be translated into SQL or any targeted database query language. A semantic parser can be complementarily used with a syntactic parser to perform semantic analysis (see Fig 2). In the architecture illustrated in Fig 2, the domain-dependent knowledge is contained in the lexicon, world model, and mapping to DB modules. The domain-independent knowledge is contained in the syntax rules (used by the lexical parser) and semantic rules (used by the semantic parser). The semantic interpreter produces a logical query that is translated to the final database query by the query generator module.

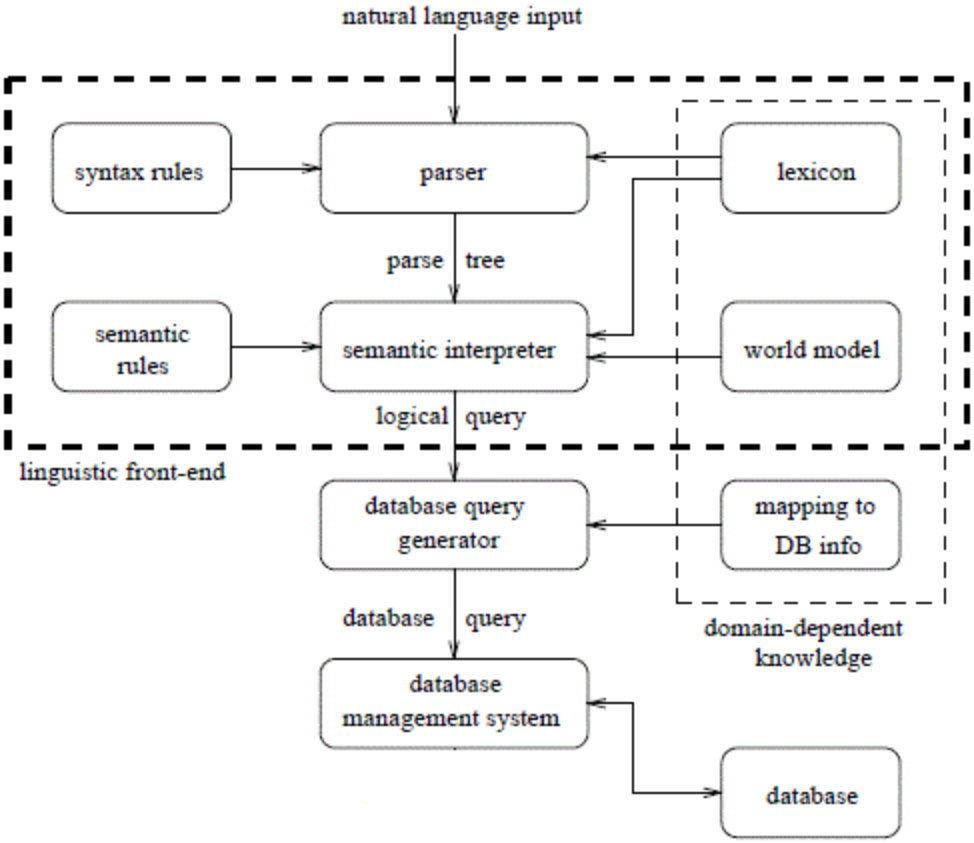


Fig 2 – Generic architecture of NLIDB combining syntactic and semantic parsing (Androutsopoulos et al, 1995)

The drawback of semantic grammar systems is the difficulty to port them to different application domains (Pazos et al., 2013). Customization requires the development of a new grammar for each new configuration. Other samples of semantic grammar based systems can be found in (Nguyen & Le, 2008) and (Minock et al., 2008).

2.1.4 NLIDB portability

Early NLIDBs were designed to interface a specific database and for only one given knowledge domain (lunar geology for LUNAR, for example). From the 1980's, research focused more on portability; the aim being to create NLIDBs that can easily adapt to a database with a different universe of discourse or even new natural language. The following sections discuss challenges related to NLIDB portability and methods developed to address the problem.

2.1.4.1 Domain portability

NLIDBS are often designed to answer questions within a particular domain (example: weather forecast, train service, etc.). A domain portable NLIDB is designed in such a way that the system can be configured easily for use in several subject domains (Androutsopoulos et al, 1995). The challenge here is to construct an effective linguistic model that includes new words and concepts pertaining to the new domain. The configuration task has to be performed by system developers, knowledge engineers or users. The quality of the linguistic model used has a tight effect on the correctness of the system. However, designing and building a model to be used by a NLI system often requires certain knowledge of computational linguistics, an understanding of the database structure and finally expertise in the formal language to query the target data source. Therefore, customizing NLI

has historically been the responsibility of a few experts. The previous situation resulted into costly system customization which hindered development and wide adoption of NLI. In response to this problem, recent research trends in NLI investigate how to reduce the effort and expertise required for building linguistic models needed to customize systems to new domains. The following paragraphs describe the various strategies developed that simplify customization to new domains.

Simple authoring systems

Simple authoring systems focus on minimizing the effort required to adapt the system to new domains by building a user-friendly authoring (or customization) interface that does not require expertise in computational linguistics. The project TEAM (Transportable English database Access Medium) is among the first NLIDB applying this strategy (Grosz, Appelt, Martin, & Pereira, 1987). Customizing TEAM requires some general knowledge of computer systems and the target database; the user is not required to have a background in computational or formal linguistics. System customization is performed by adding new verbs, adjectives and synonyms of existing words through the customization module. ORAKEL (Cimiano, Haase, Heizmann, & Mantel, 2008) is a more recent example of an easy to customize NLI. ORAKEL first auto-constructs the lexicon from the ontology targeted; this helps to simplify the task of customization which consists of mapping lexicon terms to relations specified in the ontology domain. Most of the NLIDB systems integrating a user-friendly authoring module we reviewed interface with ontologies; the relatively few systems targeting relational databases are presented in section 2.2. Further examples of NLIDB targeting ontologies with a user-friendly authoring module can be found in (Lopez et al. , 2005) and (Bernstein et al., 2005).

Interactive natural language interfaces

The interactive approach advocates building systems with a concise model and interactively cooperating with the end-user to customize the system. Consequently, systems based on this paradigm will often have a very small or no domain specific entries in the model. This design choice results in a more generic linguistic model that is easily portable to new domains.

NALIR is an interactive NLIDB to relational databases that translates natural language questions to SQL (F. Li & Jagadish, 2014). NALIR integrates a limited set of possible interactions with the user in order to assist incrementally building complex natural language questions. The interface supports advanced SQL features such as aggregations, sub-queries and queries joining multiple tables. The system also provides a natural language feedback to the user, explaining how the query was interpreted. Ambiguities in the questions are dealt with by letting the user select the correct interpretation from a list of multiple possible answers.

FREyA (Damljanovic, Agatonovic, & Cunningham, 2012) is an interactive NLI to ontologies that relies on clarification dialogs with the end user to parse queries. FREyA compared to NALIR has the advantage of learning from previous user choices to self-train and improve its model, thereby reducing the need for subsequent clarification dialogs. However, NALIR can support more complex queries compared to FREyA. Both FREyA and NALIR do provide feedbacks to user about queries' interpretations. Another example of an interactive natural language interface can be found in (Li et al, 2007).

Automatic acquisition of the linguistic model

Automatic acquisition consists of automatically constructing the model required for query parsing. One approach consists of auto-extracting the information required to build the model from the

meta-data describing a data source structure or directly from the actual data. A second approach consists of training the NLI using a corpus of annotated or non-annotated data.

Kaufmann et. al (2007) presents NLP-Reduce, a natural language interface to the Semantic Web. NLP-Reduce extracts properties from the Semantic Web to build the lexical dictionary automatically. This initial dictionary is completed by retrieving word synonyms from WordNet (Miller, 1995), an external lexical dictionary on the Web.

Freitas & Curry (2014) propose a NLI over heterogeneous linked data graphs. The system uses a large text corpus to auto-build a semantic model for the graph based on statistical analysis of co-occurring words. The lexical dictionary is extracted from an unannotated text corpus instead of an external source like with NLP-Reduce. The semantic model built allows users to express questions to the graph without prior knowledge of the underlying structure.

An example of a NLI trained with a labelled corpus is presented in (Zettlemoyer & Collins, 2012) and a NLI project based on unsupervised learning can be found in (Goldwasser et al, 2011).

Controlled natural language interfaces

A controlled natural language is a sub-set of natural language that uses a limited set of grammar rules that allows a subset of possible phrase constructions. One way of building an easily portable NLI consists of restricting the system to a controlled natural language that can be fully supported. NLyze (Gulwani & Marron, 2014) is an example of a NLI using a controlled natural language called DSL (Domain-Specific Language) to interrogate a tabular spreadsheet. Queries written with DSL use a restricted grammar (i.e. “sum the totalpay for the capitol hill baristas”) (Gulwani & Marron, 2014) but the system can be ported to any spreadsheet without the need for customization. Ginseng (Bernstein et al., 2005) uses a “quasi-natural language” to query semantic Web data sources. To cope with the necessity to first teach the user the restricted language (as the case with NLyze), Ginseng proposes a guided input interface which gives suggestions and auto-completion of the query in real-time. A project similar to Ginseng based on ontologies can be found in (Franconi et. al, 2010).

2.1.4.2 DBMS portability

A DBMS-independent NLIDB should be easily customizable to work with various underlying database management systems (Androutsopoulos et al, 1995). When SQL (the standard query language for RDBMs) is supported, it is trivial to port the NLIDB to any SQL-based DBMS. In the case of a completely new DBMS query language, only the module that translates logical intermediate queries to database queries must be rewritten. If the NLIDB architecture does not include an intermediary language, extensive modifications may be required to successfully support the new RDMS query language. Examples of NLIDBs designed to support multiple database management systems can be found in (Cimiano et al, 2008) (Hendrix et al., 1978), (Hinrichs, 1988) and (Thompson & Thompson, 1983). Most of the works on DBMS portable NLI are from the 70’s and 80’s. More recent works use ontologies to aggregate data from different sources (RDBMS, XML or Web, for example). Therefore, integrating different database models is done through an integration layer before involving the natural language interface. In consequence, there is a greater focus on developing domain independent NLIs instead of DBMS portable systems.

2.1.4.3 Natural language portability

The vast majority of research in NLP focuses on English. A natural language independent NLIDB should be easily customized to work with a new natural language. This task is complex and difficult, as it requires the modification in almost every level of the NLIDB architecture. A possible approach to create multilingual NLP is to design syntactic and semantic parser modules loosely coupled to the overall architecture. This approach allows plugging new language modules without changing the entire system. Another approach consists of using machine translation (can be an external module) to first translate the query to a target natural language. Examples of system designed to work with various natural language can be found in (Zhang et al, 2002), (Jung & Lee, 2002) and (Wong, 2005).

2.1.5 NLIDB evaluation

There is currently no generally accepted evaluation framework or benchmark for NLIDB (Pazos et al., 2013). NLIDB evaluation can focus on several facets, the most common found throughout the literature are result's accuracy, system's performance, and usability. The assessment of usability often involves user testing. The assessment of system's accuracy is the most used approach in NLIDB evaluation; it is typically performed by testing a system prototype with a set of queries from a benchmark corpus.

The most commonly used benchmark databases are geo-base, rest-base and job-base; all developed by L. Tang and R. Mooney (Tang & Mooney, 2001). The three databases are implemented in Prolog and have a simple structure (maximum 8 entity classes). When used to evaluate a NLI targeting a relational database, the databases need to be converted into a relational version. Mooney additionally provides three benchmark query corpora, one for each database. The questions from Mooney's corpora present a high degree of logical complexity and contains arguably the most challenging questions among publicly available corpora (Pazos et al., 2013). The second most used database is ATIS; which is a relational database containing information on airline flights (Hemphill et al., 1990). The ATIS database structure is more complex compared to Mooney's; it has 27 tables and 123 columns. ATIS is provided along with the largest corpus but most of the questions are repetitive using the same grammatical structures with different values (Pazos et al., 2013).

There are no benchmark metrics globally accepted throughout the field to assess NLIDBs. The two most common metrics are precision and recall whose meaning reflects the definition in information retrieval (Manning et al., 2008) (Table 2 helps clarify the definition of precision and recall in information retrieval). And again, there is no consensus on the definition of recall; the two definitions found in the literature (see Table 3) are presented in Fig 3.

Table 2 – Confusion matrix defining the notions of true positives, false positives, false negatives and true negatives (Manning et al., 2008)

	Relevant	Non relevant
Retrieved	True positives	False positives
Not retrieved	False negatives	True negatives

Table 3 gives a list of NLIDB along with the benchmark corpus, database and metric definition used for their evaluation.

Definition 1 (the most prevalent definition in NLIDB field)

$$Recall=\frac{\#(retrieved\ items)}{\#(relevant\ items)}=\frac{\#true\ positive+\#false\ positive}{\#true\ positive+\#false\ negative}$$

Definition 2 (the standard definition in information retrieval)

$$Recall=\frac{\#(relevant\ items\ retrieved)}{\#(relevant\ items)}=\frac{\#true\ positive}{\#true\ positive+\#false\ negative}$$

Definition of precision

$$Precision=\frac{\#(relevant\ items\ retrieved)}{\#(retrieved\ items)}=\frac{\#true\ positive}{\#true\ positive+\#false\ positive}$$

Fig 3 – Definitions of precision and recall

Table 3 – List of NLIDB and their benchmark database, sample query corpus and evaluation metric definition

NLIDB	Benchmark database	Benchmark query corpus	Metric definition
COCKTAIL (Tang & Mooney, 2001)	Geo-query and Jobs-query	Geo-query and Jobs-query	2
PRECISE (Popescu et al., 2003)	Geo-query, Rest-query and Jobs-query (converted to a relational version)	Geo-query, Rest-query and Jobs-query	1
GINSENG (Bernstein et al., 2005)	Geo-query and Rest-query (converted to OWL)	Geo-query and Rest-query	1
KRISP (Kate & Mooney, 2006)	Clang and Geo-query	Clang and Geo-query	2
PRECISE ATIS (Popescu et al., 2004)	ATIS	ATIS	1
(Chandra, 2006)	Geo-query	Geo-query (175 queries)	2
PANTO (Wang et al., 2007)	Geo-query, Rest-query and Jobs-query (converted to ontology, OWL format)	Geo-query, Rest-query and Jobs-query	1
(Minock et al., 2008)	Geo-query	Geo-query (250 queries)	1
FREYA (Damljanovic et al., 2012)	Geo-query	Geo-query (250 queries)	2
(Giordani & Moschitti, 2010)	Geo-query	Geo-query (250 queries)	1
(Giordani & Moschitti, 2012)	Geo-query	Geo-query (800 queries)	1
Ask Me (Llopis & Ferrández, 2013)	ATIS	ATIS	1

2.2 Approaches toward domain portable NLI to RDB

This section reviews NLI to relational databases using approaches similar to the present research work; the common problems and strategies used to solve them are presented as well; and finally the strengths and weaknesses of diverse approaches similar to this research are discussed.

2.2.1 Early attempts to transportable NLIDB

TEAM (Grosz et al., 1987) is a foundational earlier work that addressed in the most exhaustive way the challenges related to transportable NLIDBs. The TEAM project hypothesized that if a NLI is built in a sufficiently well-principled way, the information required to customize it can be provided by a user with general expertise about computer systems and the particular database, but without special knowledge on computational linguistics. This hypothesis is still used in recent works on portable NLIDB (Cimiano et al., 2008) (Minock et al., 2008). The TEAM's architecture comprises two major modules: DIALOGIC and Schema Translator. The DIALOGIC's module leverages Paxton's parser (Paxton, 1974) and also performs a few basic programmatic functions and quantifier scope resolution. Fig 4 shows a parse tree corresponding to the query "Show each continent's highest peak". The schema translator module first translates the parse tree to a first-order logic query, then translates the logical query to SODA (the formal language to query the underlining database). Fig 5 shows an example of the translation process.

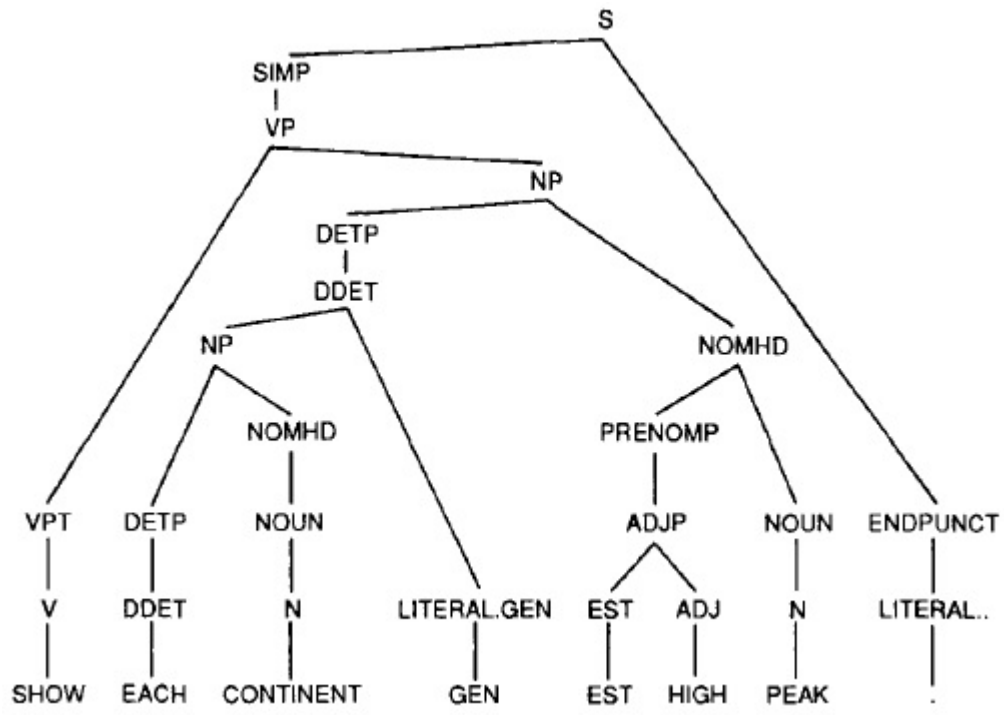


Fig 4 – Example of parse tree from TEAM (Grosz et al., 1987)

To verify its core hypothesis, TEAM developed a user-friendly authoring system that required from the user only a general knowledge on computers and understanding of the targeted database. The system pre-included a domain-independent knowledge base. Customization consisted of completing domain related knowledge including synonyms for database objects, new verbs, and their meaning. Fig 6 shows the screen for acquiring new verbs; which is performed in a question-response fashion to guide the user through customization. As illustrated below, TEAM collects the base form of the verb along with the conjugated forms.

```
(QUERY
  (ALL +WORLDC-CONTINENT+2
       (+WORLDC-CONTINENT+ +WORLDC-CONTINENT+2)
       (WH +PEAK+1
            (AND (+PEAK+ +PEAK+1)
                 (((*SUPER* (*MORE* *HIGH))
                   +PEAK+5
                   (AND (+PEAK+ +PEAK+5)
                        (*PKCONT-CONTINENT-OF +PEAK+5 +WORLDC-CONTINENT+2)))
                  +PEAK+1))
            T)))

FOR EVERY CONTINENT
  WHAT IS EACH PEAK
  SUCH THAT THE PEAK IS THE HIGHEST PEAK SUCH THAT
    THE CONTINENT IS CONTINENT OF THE PEAK?

SODA query:
((IN #: $1 CONT) (MAX (#: $3 PEAK-HEIGHT)
                      (IN #: $2 WORLDC)
                      (IN #: $3 PEAK)
                      ((#: $3 PEAK-COUNTRY) EQ (#: $2 WORLDC-NAME))
                      ((#: $2 WORLDC-CONTINENT) EQ (#: $1 CONT-NAME)))
                (? (#: $1 CONT-NAME))
                (? (#: $3 PEAK-HEIGHT))
                (? (#: $3 PEAK-NAME)))
```

Fig 5 – Translation of logical query to SODA query in TEAM (Grosz et al., 1987)

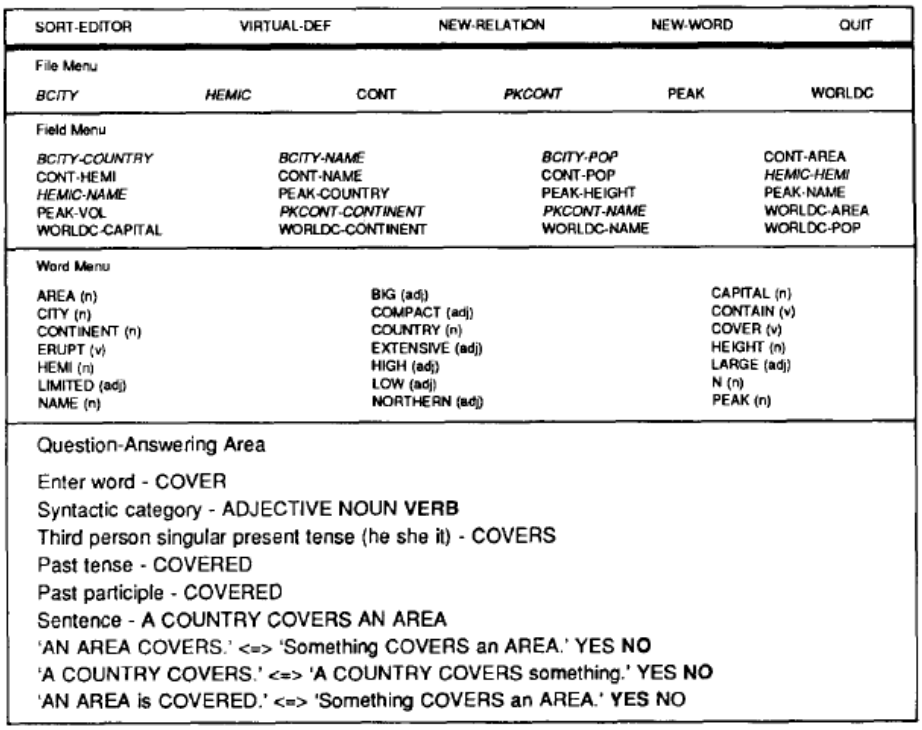


Fig 6 – System customization screen in TEAM: acquisition of a new verb

TEAM offered support for aggregation functions and methods to handle superlative and comparative forms of adjectives, but did not support more advanced features like nesting and sorting. To simplify handling superlative and comparative forms of adjectives, TEAM includes two additional parameters into its lexicon: firstly a link to a predicate that quantifies the adjective (e.g. *the field 'montainLength' for 'big mountain'*) and secondly a 'scale direction' for the predicate (e.g. *positive for tall and negative for short*). TEAM did not undergo a systematic testing (Grosz et al., 1987); this makes it hard to have a clear idea of the actual performances of the system. Table 4 presents a comparison of TEAM with other early portable NLIDB.

Table 4 – Comparison of TEAM with other early transportable systems (Grosz et al., 1987)

	TEAM	Ginsparg	IRUS	CHAT-80	ASK	LDC-1	EUFID
Types of portability	Linguistic domain, db, DBMS	Linguistic domain, db, DBMS (Relational)	Linguistic domain, db, DBMS	Linguistic domain, db	Linguistic domain, db	Linguistic domain, db	Linguistic domain, db, DBMS
Expertise of transporter	Db expert	System designer	System designer	System designer	User, super user, system designer	Super user	System designer, domain expert
Information acquired	Lexical, conceptual, db schema	Lexical, semantic network, db schema	Lexical, domains semantics, db schema	Lexical, logical form to db predicate mapping	Lexical, conceptual, db schema	Lexical, conceptual, conceptual to db mapping	Lexical, semantic graph, database
Time to adapt	Minute-hours	Hours-days	Weeks	Days-weeks	-	Minutes-hours	months

In the above table:

a system designer: refers to a user with a general knowledge of computer systems who received a training to customize the system;

a super user: refers to an advanced end user who is more knowledgeable in computer systems;

a domain expert: refers to a simple user or super user with expertise in the target domain knowledge.

2.2.2 NLIDB using a semantic graph as domain knowledge model

Barthélemy et al (2005) defines a semantic graph as "a network of heterogeneous nodes and links" containing semantic information. The semantic graph structure is used in the literature to model the domain knowledge. The semantic graph is used for its intuitive structure that makes it easy to build and extend even by a user with no background in computational linguistics. EUFID (Templeton & Burger, 1983) is among the earliest NLIDB to use semantic graph to model the domain knowledge.

The semantic graph structure in (Zhang et al., 1999) (see Fig 7) has the particularity of including weights to the links to express their strength or likelihood. During query analysis, the system first searches for key terms in the user's input (like concepts in the semantic graph, database attributes, and values). The query is therefore viewed as a set of unconnected semantic graph nodes. The system uses the information from the semantic graph to build several possible subgraphs by including links between disconnected nodes. The weights of the links in the domain model are used to compute a ranking for each subgraph. The highest ranked subgraph is selected and translated into the final query. The system supports aggregation, but not nesting. The NLIDB has not been

thoroughly evaluated: the test consisted of running 30 queries from an unsaid number of candidates which all have been correctly answered. It is, therefore, hard to clearly evaluate the real capability of the system.

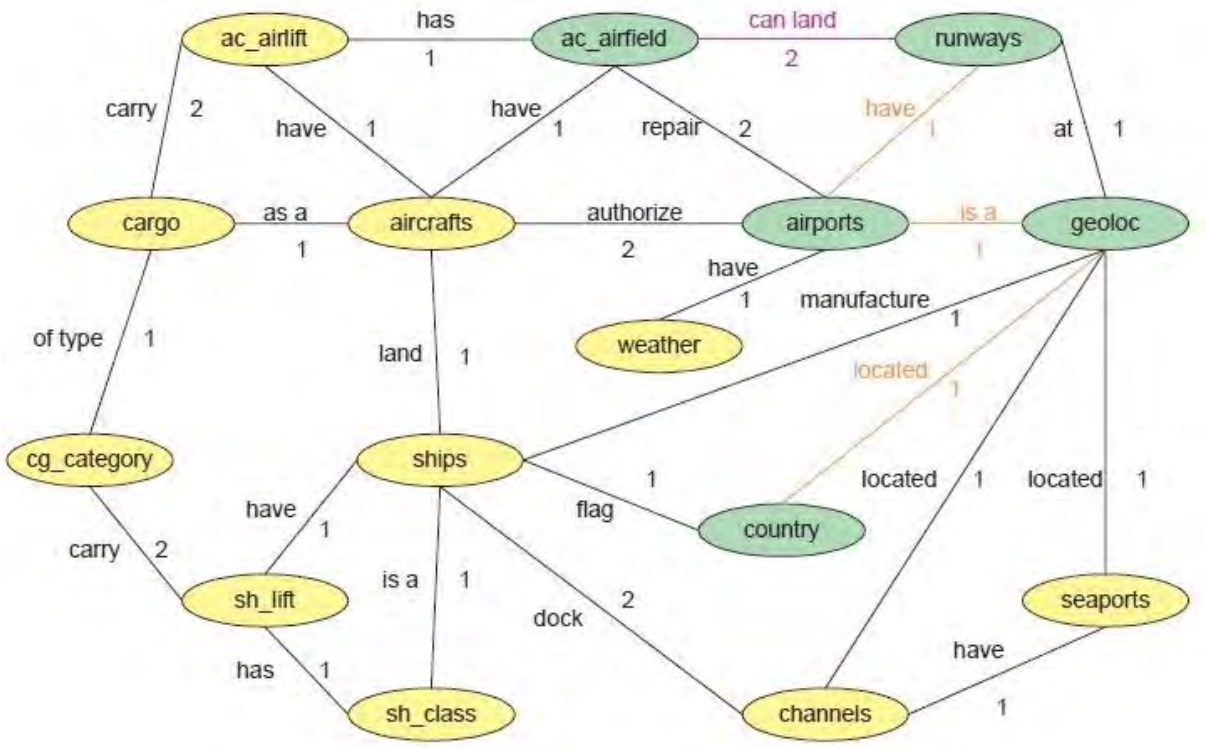


Fig 7 – Example of semantic graph structure (G. Zhang et al., 1999)

Meng & Chu (1999) also present a portable NLIDB targeting a SQL database which uses a semantic graph to model the domain's knowledge. The graph's structure in (Meng & Chu, 1999) is composed of nodes (representing database tables), database attributes, and links (see Fig 8). The squares represent the tables and circles represent the database attributes. The system in (Meng & Chu, 1999) retrieves from the natural language input three components: the query topics, the select list and the query constraints. A query topic corresponds to a subgraph of the semantic graph containing the keywords found in the user's query. This subgraph allows retrieving joins between tables automatically (Fig 9 shows an example of subgraph). The query constraints are retrieved using values from the database found in the query (translated to "sourceColumn = 'valueFound'"). And finally, any other column mentioned in the query but not part of constraints are assumed to be part of the select clause. The information gathered in query topics, select list, and query constraints are used to build the final SQL query.

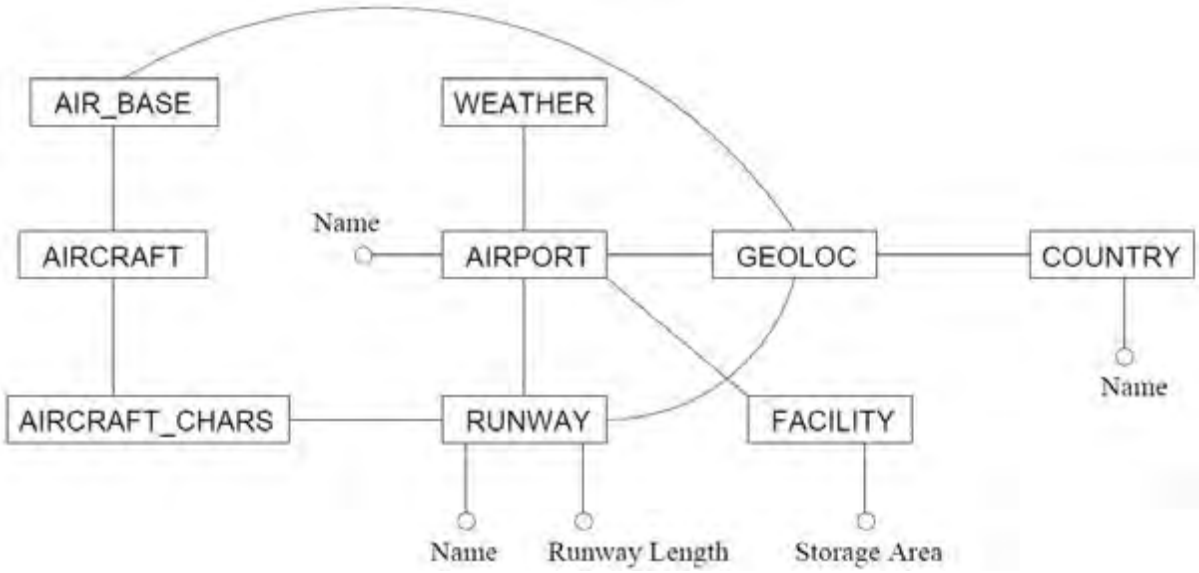


Fig 8 – Semantic graph structure of (Meng & Chu, 1999)

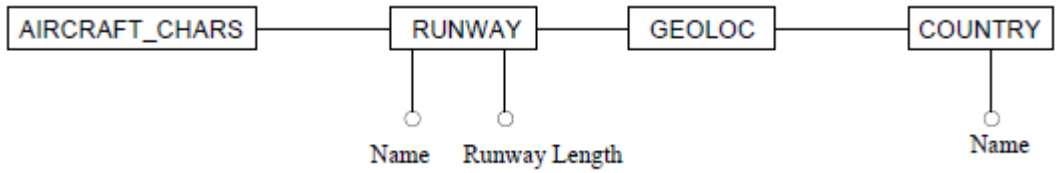


Fig 9 – Example of subgraph corresponding to a query about runaways and aircrafts (Meng & Chu, 1999)

The approach used in (Meng & Chu, 1999) uses only the semantic graph as the source of information describing the domain knowledge in order to translate natural language questions to SQL; no additional grammar is required. However, the prototype built supports only simple SELECT FROM WHERE queries and there is no evaluation of the system available to assess its performance.

2.2.3 Portable NLIDB based on semantic parsers

Semantic parsers include production rules that can translate a natural language query to a formal query in a meaning representation language like first-order logic. NLIDBs based on this approach are relatively straightforward to develop.

Minock et al. (2008) present a good example of a portable NLI to SQL using a semantic parser that is defined with Lambda Synchronous Context-Free Grammar. The parser maps the user query to a variant of Codd's tuple calculus which includes higher order predicates like "LargestByArea". The system's objective is to allow an everyday technical team member to build a robust NLI. A lot of attention has been put on constructing a user-friendly authoring module based on light annotations. The system customization is completed in three steps: naming, tailoring and defining. The naming phase provides synonyms to database attributes, joins, and facts from the database. Tailoring consists of mapping patterns from the natural language query to their corresponding concepts expressed in tuple calculus (see illustration in Fig 10). Finally, the defining phase allows adding more definitions to the system using natural language. An example of a possible definition borrowed from (Minock et al., 2008) is "define a 'major' state as a state with more than 1 million people".

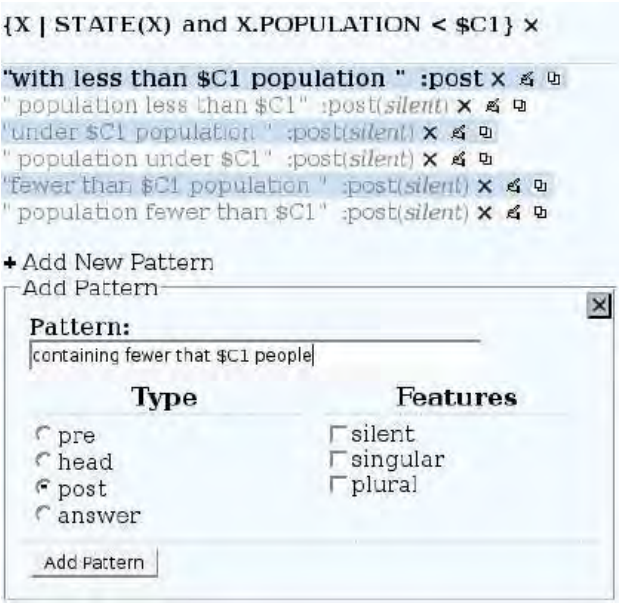


Fig 10 – Tailoring operation in (Minock et al., 2008)

To evaluate the system, two subjects had been requested to customize the system by manually tailoring 100 random queries from the geo-query corpus (Tang & Mooney, 2001). The subjects, who were undergraduate students with a background in databases, have taken two hours to customize the system. The accuracy yielded on various testing set varied between 80% and 90%. However, it must be noted that the prototype included complex concepts in the parser in the form of higher order predicates. For example, the semantics for all the superlative forms were pre-loaded, this alone can explain the high accuracy observed.

Another example of portable NLI to SQL based on a semantic parser can be found in (Nguyen & Le, 2008) where the system uses a domain-independent semantic grammar and can be used with no customization.

An important drawback with semantic parsers is that the use of rigid production rules makes the system less robust against noise and unknown structures. The empirical methods presented in the next section address this problem.

2.2.4 Empirical approaches toward portable NLIDB

An empirical approach allows training a model using a corpus and therefore the NLI is generic and portable. Empirical approaches are gaining importance in NLP again with much recent research work focusing on statistical approaches to process natural languages. This trend is explained by the high complexity of language making it difficult to capture a full range of natural language contexts and their corresponding semantic concepts when using a limited set of predefined rules (Kate & Mooney, 2006).

Giordani & Moschitti (2010) use machine learning algorithms to train a semantic parser that translates natural language queries to SQL. The training is achieved using Support Vector Machines (SVM), a supervised learning method (Smola & Vapnik, 1997). The training set used is composed of a set of pairs $P = N \times S$ where *N* represents the set of parse trees of natural language queries parsed with Charniak's syntactic parser (Charniak, 2000) and *S* represents the set of parse trees of the corresponding SQL query. Fig 11 shows an example of a pair (n_i, s_i). An experiment with a model trained with 250 queries from geo-query (Tang & Mooney, 2001) achieved 76% accuracy.

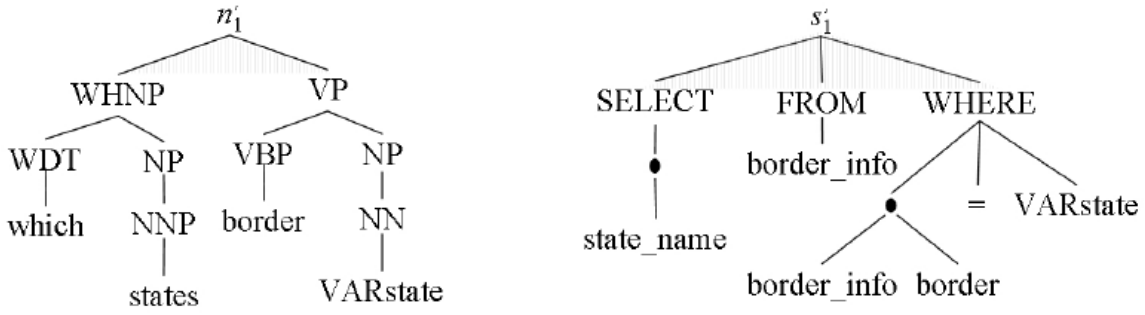


Fig 11 – Parse tree of a natural language query and its SQL query (Giordani & Moschitti, 2010)

KRIPS is a more generic system based on machine learning that is trained with pairs composed of the natural language queries and their corresponding formal queries in a given Meaning Representation Language (MRL) (Kate & Mooney, 2006). The system accepts any MRL that can be defined with a deterministic Context-Free Grammar (CFG) in order to ensure that each MRL query will have a unique parse tree.

Statistical approaches offer the advantage of being more robust to noise (sentence with typos, for example) and uncertainty (like unseen grammatical structures). The main drawback of this approach is the need to build a large annotated corpus with questions related to the subject domain for customization. This task is especially costly when correct formal queries (like SQL or first-order logic) need to be manually produced.

2.2.5 NLIDB based on dependency grammars

Dependency grammars (DG) are the fruits of developments in syntactic theories. The work of Tesnière (1959) greatly contributed to the development of DG. The focus in DG is on the analysis of dependency relationships between words in the sentence with the verbs being the structure center of the dependency trees. Fig 12 illustrates the dependency tree generated by the Stanford dependency parser (De Marneffe et al., 2006) for the query "Which states border the state with the most rivers?" from geo-query corpus (Tang & Mooney, 2001).

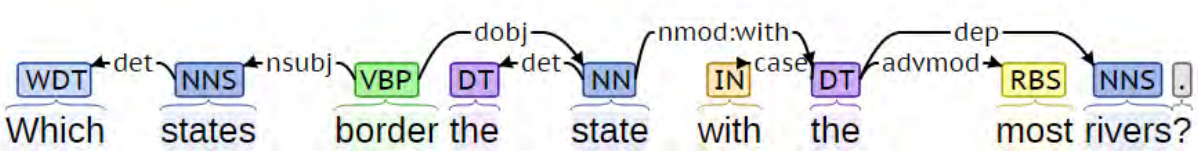


Fig 12 – Example of dependency tree from the Stanford dependency parser

Giordani & Moschitti (2012) presents a NLIDB to SQL based on dependency grammar that uses the Stanford parser. The system uses the metadata in the RDMS describing the database as source of synonyms to build its lexicon. The prototype supports complex queries, including nesting, aggregation, and negation. For each query, up to 10 possible results ranked by their relevance are produced. The experimental result with geo-query showed that 81% of the responses ranked as the best answers are correct. The accuracy increases to 92% for the 3 first responses and 99% for the 10 best results. An intermediary MRL was not used; the system relies on a custom made algorithm (see (Giordani & Moschitti, 2012) for details) which analyses the dependency parse tree and produces the final SQL. The result obtained shows the potential power of dependency parsers. However, the

prototype does not feature an authoring module to customize the system. The only input used is the metadata in the RDBM. Therefore, additional semantic rules to support special cases are directly hard coded in the engine. This approach makes the system less portable. A similar work can be found in (Gupta et al., 2012), where the authors present a NLIDB to SQL using a dependency framework called "Computational Paninian Grammar" which used the Stanford Typed Dependency (STD) parser (De Marneffe et al., 2006) in the background. The semantic analysis here consists of mapping elements from the dependency tree to the domain's conceptual model retrieved from the database schema. The mapping rules are encoded in the semantic frames (see an example in Table 5). Each verb has a role "root" and is associated to his subject and object that have the roles K1 and K2. The concepts are mapped to their query terms and possible values they can have.

Table 5 – Example of semantic frames for the relation "teach" and "register" (Gupta et al., 2012)

Role	Concept	Query Term	Value
Root	teach		-
K1	faculty	faculties	-
K2	course	-	NLP
Root	register	took	
K1	student	students	which
K2	course	-	NLP

The interest of the semantic frames approach is that it offers a simple and straightforward framework that simplifies expressing semantic mapping rules.

2.3 Literature review synthesis

The overall area of NLP research remains very experimental. Even though there are several usable commercial systems available, unrestricted use of natural language is still an open problem. Sujatha (2012) points out the following general open problems that still require extensive research:

- NLIDB portability: involves development of NLIDB that can easily adapt to multiple domains, underlying RDMS and natural languages;
- Error reporting and handling: give to the user a clear explanation when a query cannot be handled to help him/her adapt his/her questions;
- Disambiguation when large domains are considered.

The last two decades have witnessed interest in developing easily portable NLI. However, most of the works focus on NLI targeting ontologies, but there is relatively less work on portable NLI targeting relational databases.

The review of portable NLI to relational databases shows a trade-off between portability and coverage. Highly portable systems tend to achieve a relatively smaller coverage and accuracy. For example, systems using a semantic graph like in (G. Zhang et al., 1999) and (Meng & Chu, 1999) use a domain knowledge model that is intuitive and easy to build by a user with no expertise in linguistics. As a consequence, the system built is easily portable. However, the model's simplicity prevents expressing advanced concepts which results in lower coverage. A similar difficulty is found in (Gupta et al., 2012), where the use of semantic frames simplifies customization while also hindering the system's coverage.

Approaches ensuring coverage of complex queries require an important effort for customization. The approaches reviewed yielding interesting coverage include NLIDB based on semantic grammars and empirical approaches. As a general rule of thumb, semantic parser based systems are required to include a very large set of rules to achieve a decent accuracy (Pazos et al., 2013). This translates into increased customization work. The authoring module plays a key role for semantic parser based systems; as a user-friendly customization module can positively impact the system's portability. The system in (Minock et al., 2008) uses Codd's tuple calculus to define semantic production rules. In consequence, a background in computational linguistics is required which limits the number of potential users capable to set up the system. The systems based on empirical approaches such as in (Giordani & Moschitti, 2010) and (Kate & Mooney, 2006) are promising and can support very complex query constructions. However, they do require important upfront work to build the training corpus. The accuracy achievable is directly dependent on the size and quality of the training corpus.

The literature shows that nowadays parsing techniques (both syntactic and semantic) when supplied with enough production rules can achieve a remarkable accuracy (recall above 90%) with English. The problem resides in building an exhaustive model with little customization effort and expertise. Finally, the literature review shows a lack of supporting experimental results for portable NLI targeting relational databases; this was the case for most the systems reviewed. A recent review of the state of the art in NLIDB (Pazos et al., 2013) emphasise the urgent need for more annotated corpora of sample queries in diverse domains.

Chapter 3 Design of the authoring system

The review of the literature shows that it is presently possible to achieve good results when the correct quantity and quality of production rules are provided. However, constructing an effective linguistic model requires both time and expertise. This research contributes toward firstly the reduction of the workload needed to customize NLIDB and secondly retaining a decent system coverage. Chapter 3 presents an authoring system which addresses simplification of customization; the coverage aspect is addressed in chapter 4. The authoring systems presented in this chapter produce a configuration model that is used by the processing pipeline presented in chapter 4 (see Fig 21). The first section presents the design objectives and system architecture. Following is the presentation of data structures used in the design. The third and fourth sections present the top-down and bottom-up authoring approaches.

3.1 Design objectives and system architecture

The authoring system design has the objective of reducing the workload involved when configuring a NLIDB system to a new domain. Two authoring approaches are proposed to attempt achieving this objective. The architecture of the configuration module proposed is illustrated in Fig 13.

The first authoring approach proposed is called *top-down*; it investigates the possibility to use a pre-existing corpus of questions to simplify configuration. A corpus of questions contains actual terms used by end-users to reference the concepts modelled in the database. The top-down authoring approach explores the possibility of minimizing the customization workload by pre-harvesting key terms (nouns, adjectives, and verbs) from a sample corpus so that the configuration work is reduced to mapping the terms found to database concepts and their corresponding meaning. The use of sample corpus to support customization is found in the literature mainly with empirical systems (Giordani & Moschitti, 2010) (Kate & Mooney, 2006) (Chandra, 2006) (Tang & Mooney, 2001). Most of the related work reviewed uses an annotated corpus in order to train a statistical model. Manually annotating a corpus is a costly task; we propose with top-down design to use the sample corpus as-is and avoid the annotation workload. The top-down approach does not use the corpus to train automatically a new configuration model as with statistical approaches; but pre-harvests terms in order to construct a lightweight configuration framework. The top-down attempts to further reduce the work load by automatically including the configuration for negative form of verbs, superlative and comparative form of adjectives.

The second authoring approach presented is called *bottom-up;* it explores the possibility of auto-building completely a model with no manual customization. The bottom-up approach automatically retrieves the configuration information from the database schema and from WordNet. The exploitation of an external lexicon to automatically include new terms has been successfully used to improve accuracy in several works mainly targeting ontologies (Wang et al., 2007) (Palaniammal & Vijayalakshmi, 2013) (Ramachandran & Krishnamurthi, 2014) (Paredes-Valverde et al., 2015). Bottom-up investigates the effectiveness of this approach with a relational database.

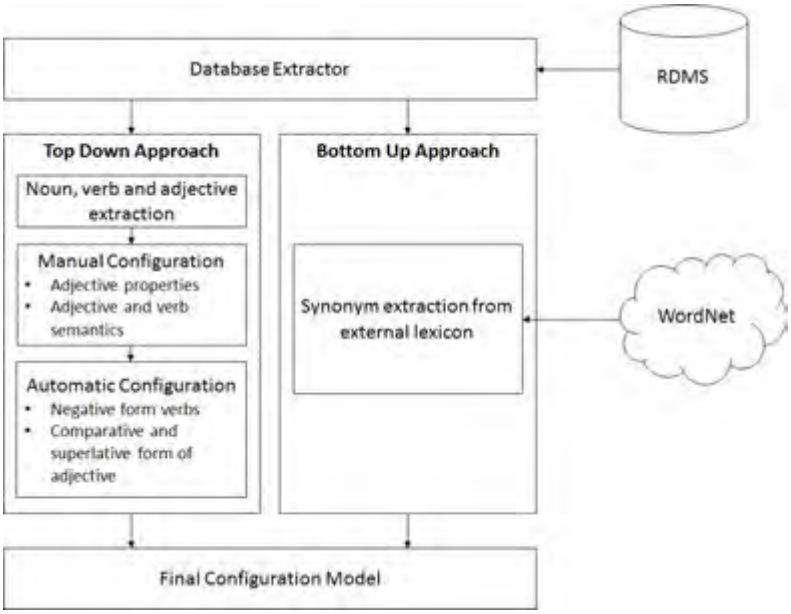


Fig 13 – Architecture of authoring system with top-down and bottom-up approach

3.2 Design of data structures for configuration

The authoring system for both top-down and bottom-up approaches generates configuration data which includes a representation of the database schema, the list of adjectives and verbs along with their respective meanings. The next sections present the data model for each component of the configuration.

3.2.1 Data structure for the database schema

The data structure representing the database schema is illustrated in Fig 14. The database model is a collection of tables which are themselves collections of columns.

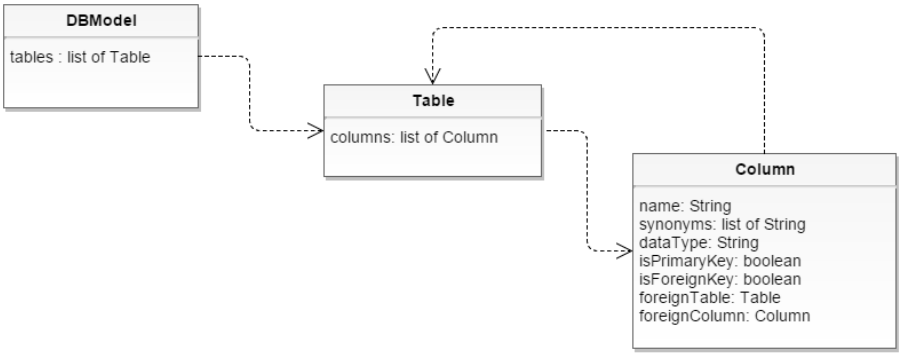


Fig 14 – Structure of the database model in memory

3.2.2 Data structure for adjectives

The structure storing adjectives includes the following elements:

- adjective: the adjective's base form;
- superlative form: the adjective's superlative form;
- comparative form: the adjective's comparative form;
- described column: the database column the adjective describes;

- a flag indicating if the adjective is scalar or not: a ‘scalar’ adjective in this context describes an adjective implicitly referring a numerical value (i.e. “large city” refers to cityArea). The notion of scalar adjective is similar to the one in TEAM (Grosz et al., 1987);
- scalar column: indicates which database column contains the numerical values described by the adjective;
- scale direction: can either be ‘positive’ (or true) or ‘negative’ (or false); a positive scale means that a superlative form of the adjective indicates a greater value of the scalar column;

Example: smart student
Adjective details:
- adjective: smart;
- superlative: smartest;
- comparative: smarter;
- describedColumn: t_student.studentName;
- isScalar: true
- scalarColumn: t_student.averageMark;
- scalarDirection: true (because smartest indicates greater averageMark);

3.2.3 Data structure of verbs

The structure storing verbs is described in Fig 15, it includes the following elements:

- verb: the verb’s base form;
- verb’s subject: a noun acting as the verb’s subject;
- verb’s object: a noun acting as the verb’s object;

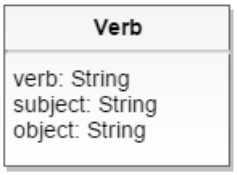


Fig 15 – Data structure of a verb

Example: student registers to faculty
- verb: register;
- subject: student;
- object: faculty;

3.2.4 Representation of meaning in the configuration

Both adjectives and verbs can optionally be associated to a meaning which represents a conditional expression. We propose the use of SQL to express meaning during configuration. This design choice allows an administrator with knowledge in databases and SQL to customize the system without needing additionally a background in computational linguistics. The meaning is expressed in a subset of SQL whose formal definition is presented in the context-free grammar in Listing 1. The SQL subset used does not include a FROM clause which is automatically generated during query parsing. The meaning can be defined as a simple or complex SQL conditional expression. A simple conditional expression has the form “DB_COLUMN COMPARISON_OPERATOR OPERAND” like in “studentMark >

10". A complex conditional expression includes nesting and can have the form "EXISTS/NOT EXISTS (NESTED_QUERY)" or "DB_COLUMN COMPARISON_OPERATOR (NESTED_QUERY)". Example of SQL expression for smartest student: "studentId IN (SELECT studentId ORDER BY studentMark DESC LIMIT 1)".

```
root : WHERE WHERE_CLAUSE ;
WHERE : 'WHERE';
WHERE_CLAUSE :CONDITIONAL_EXPRESSION  | WHERE_CLAUSE LOGICAL_OPERATOR
WHERE_CLAUSE   | PAR_L WHERE_CLAUSE PAR_R;
CONDITIONAL_EXPRESSION :  EXITS_OR_NOT PAR_L SQL_QUERY PAR_R
| DB_COLUMN COMPARISON_OPERATOR OPERAND;
LOGICAL_OPERATOR : 'AND' | 'OR';
PAR_L : '(';
PAR_R : ')';
EXITS_OR_NOT : 'NOT EXISTS' | 'EXISTS' ;
SQL_QUERY :  SELECT SELECT_CLAUSE  | SELECT SELECT_CLAUSE WHERE WHERE_CLAUSE
   | SELECT SELECT_CLAUSE ORDER_BY LIST_COLUMNS
   | SELECT SELECT_CLAUSE LIMIT LIMIT_CLAUSE
   | SELECT SELECT_CLAUSE WHERE WHERE_CLAUSE ORDER_BY LIST_COLUMNS
   | SELECT SELECT_CLAUSE WHERE WHERE_CLAUSE LIMIT LIMIT_CLAUSE
   | SELECT SELECT_CLAUSE ORDER_BY LIST_COLUMNS LIMIT LIMIT_CLAUSE
   | SELECT SELECT_CLAUSE WHERE WHERE_CLAUSE ORDER_BY LIST_COLUMNS LIMIT
LIMIT_CLAUSE;
DB_COLUMN : [a-z0-9_]+.[a-z0-9_];
COMPARISON_OPERATOR : 'NOT IN' | 'IN' | '>=' | '<=' | '<>' | '<' | '>' | '=';
OPERAND :  VALUE_OPERAND
| COLUMN_OPERAND
| SUB_QUERY_OPERAND;
SELECT : 'SELECT';
SELECT_CLAUSE :  SELECT_COLUMN   | SELECT_CLAUSE COMMA SELECT_CLAUSE;
ORDER_BY : 'ORDER BY';
LIST_COLUMNS :  DB_COLUMN
  | LIST_COLUMNS COMMA LIST_COLUMNS;
LIMIT : 'LIMIT';
LIMIT_CLAUSE : [0-9]+;
VALUE_OPERAND : [.*\\\"(.*)\\\".*"];
COLUMN_OPERAND : DB_COLUMN;
SUB_QUERY_OPERAND : PAR_L SQL_QUERY PAR_R;
SELECT_COLUMN :  AGR_FUNC PAR_L DB_COLUMN PAR_R   | DB_COLUMN;
COMMA : ',';
AGR_FUNC : 'SUM' | 'AVG' | 'MAX' | 'MIN' | 'COUNT';
```

Listing 1 – Context-Free Grammar defining the subset of SQL used to define semantics during system configuration

3.3 Design of the top-down authoring approach

The top-down authoring approach assumes the existence of a corpus of sample queries available during customization. The corpus is used to harvest nouns, adjectives and verbs from sample questions. The harvesting of lexicon elements simplifies customization which thereby consists of mapping nouns to the database objects and including meaning for certain adjectives and verbs.

3.3.1 Lexicon element harvesting

The harvesting and storage of nouns from sample queries is described in Listing 2. The part of speech tagging is performed by the Stanford POS tagger[3] which associates a tag representing the grammatical category of each word using Penn Treebank tag set (Santorini, 1990). The nouns have a tag starting with "NN". Each unique noun is stored and represents a potential database column synonym.

```
For Each sentence in corpus
  posSentence = partOfSpeechTagging(sentence)
  For Each token in posSentence
    If token.getTag().startsWith("NN") Then
      listOfNoun.addUniqueValue(token.getValue())
    End if
  End For
End For
```

Listing 2 – Noun harvesting algorithm

The adjective harvesting module leverages the Stanford dependency parser (De Marneffe et al., 2006) to find the relationships between words in the sentence. Listing 3 presents the adjective harvesting algorithm.

```
For Each sentence in corpus
  Call StanfordDependencyParser(sentence)
  For Each token in POS(sentence)
    If token.getTag().isAdjective()
      Adjective adj = new Adjective(token.getTag().getWord())
      String describedWord = getDescribedNoun()
      adj.setDescribedWord(describedWord)
      listAdjectives.addUniqueValue(adjective)
    End If
  End For
End For
```

Listing 3 – Adjective harvesting algorithm

The dependency parser firstly performs part of speech tagging to categorize each word in the sentence. The adjectives have a tag starting with "JJ" ("JJ" = adjective base form, "JJR" = adjective in comparative form and "JJS" = adjective in superlative form). The noun associated with the adjective can be found by retrieving the adverbial modifier (encoded as "amod") dependency relationship ending in the adjective as illustrated[4] in the example in Fig 16.

Example: what is the longest river ?

[3] The Stanford POS tagger is distributed under a General Public Licence and can be freely downloaded from http://nlp.stanford.edu/software/tagger.shtml

[4] The visualizations are produced with DependenSee, a java API developed by Awais Athar available here: http://chaoticity.com/dependensee-a-dependency-parse-visualisation-tool/

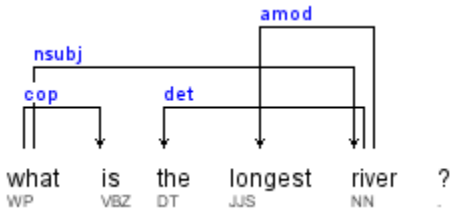


Fig 16 – Typed dependency graph for query "what is the longest river ?"

The harvesting of verbs leverages the Stanford dependency parser as well. The algorithm harvesting verbs is presented in Listing 4. The part of speech tagger assigns verbs with a tag starting with "VB". The subject and object of the verb are respectively referred by the relation "nsubj" and "nobj" in the typed dependency query as illustrated in Fig 17.

Query: which state has the longest river?

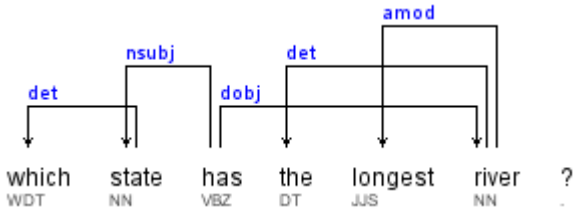


Fig 17 – Typed dependency graph for query "which state has the longest river?"

```
For Each sentence in corpus
  Call StanfordDependencyParser(sentence)
  For Each token in POS(sentence)
    If token.getTag().startsWith("VB") Then
      Verb verb = new Verb(token.getTag().getValue())
      verb.retrieveVerbSubject()
      verb.retrieveVerbObject()
      listVerbs.addUniqueValue(verb)
    End If
  End For
End For
```

Listing 4 – Verb harvesting algorithm

The sub-routines retrieveVerbSubject and retrieveVerbObject retrieve the noun pointed by respectively the "nsubj" and "nobj" relation in the parsed query.

3.3.2 Steps in system configuration with top-down approach

The manual configuration of the system starts after the harvesting phase is completed and it includes mapping of nouns to database columns, capture of adjective information and inclusion of adjective and verb meanings.

Mapping of nouns to database columns

The nouns harvested are used to include synonyms to database columns. The interface mapping nouns to columns is shown in Fig 18. The system administrator is presented with a list of nouns harvested followed by a list of available database columns.

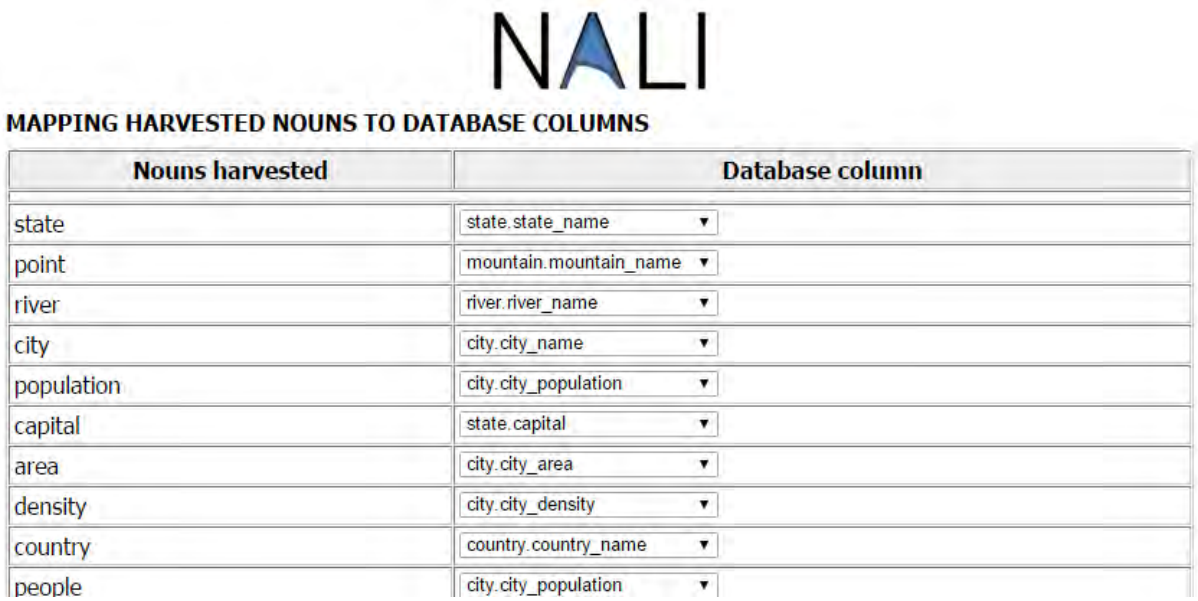


Fig 18 – User interface mapping nouns to database columns

Capture of additional adjective information

The phase of adjective information capture allows the administrator to set the scalarFlag and when applicable, the scalar column and direction (see
Fig 19). When the adjective's base form is harvested, the system automatically builds the comparative and superlative form. The algorithm for building comparative and superlative are presented respectively in Listing 5 and Listing 6.

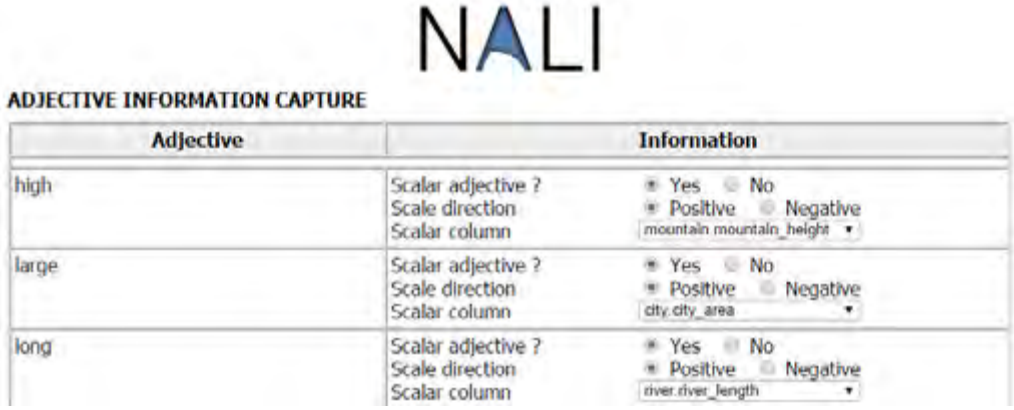


Fig 19 – User interface capturing adjective information

```
Function constructSuperlative(adjective)
  If getSyllableNumber (adjective) > 2 Then
    return "more" + adjective
  Else If getSyllableNumber (adjective) = 2 And isConsonant(lastLetter(adjective)) Then
    return "more" + adjective
  End If

  If isConsonant(lastLetter (adjective)) Then
    If isConsonant(secondLastletter(adjective))Then
      return adjective + secondLasLetter(adjective)+"er"
    Else
      return adjective + "er"
    End If
  Else If endsWithY(adjective) Then
    return removeLastY(adjective) + "ier"
  Else If endsWithE(adjective) Then
    return adjective + "r"
  End If
End Function
```

Listing 5 – Algorithm constructing the comparative form of adjective

```
Function construct_superlative(adjective)
  If getSyllableNumber(adjective) > 2 Then
    return "most" + adjective
  End If

  If isConsonant(lastLetter (adjective)) Then
    If isConsonant(secondLastletter(adjective)) Then
      return adjective + secondLasLetter(adjective)+"est"
    Else
      return adjective + "est"
    End If
  Else If endsWithY(adjective) Then
    return removeLastY(adjective) + "iest"
  Else If endsWithE(adjective) Then
    return adjective + "st"
  End If
End function
```

Listing 6 – Algorithm constructing the superlative form of adjective

3.3.2.1 Inclusion meaning for adjectives and verbs

The administrator adds the meaning expressed as a SQL conditional expression to certain adjectives and verbs harvested using the interface illustrated in Fig 20. Not all the adjectives and verbs need to have a meaning explicitly included. In addition, the engine automatically builds the meaning for negative form of verbs, superlative and comparative form of adjectives using the meaning provided for the base forms. Automatically building the meaning reduces the workload for authoring the system. Listing 7 presents the algorithm building the verb's negative form from semantic provided for the base form.

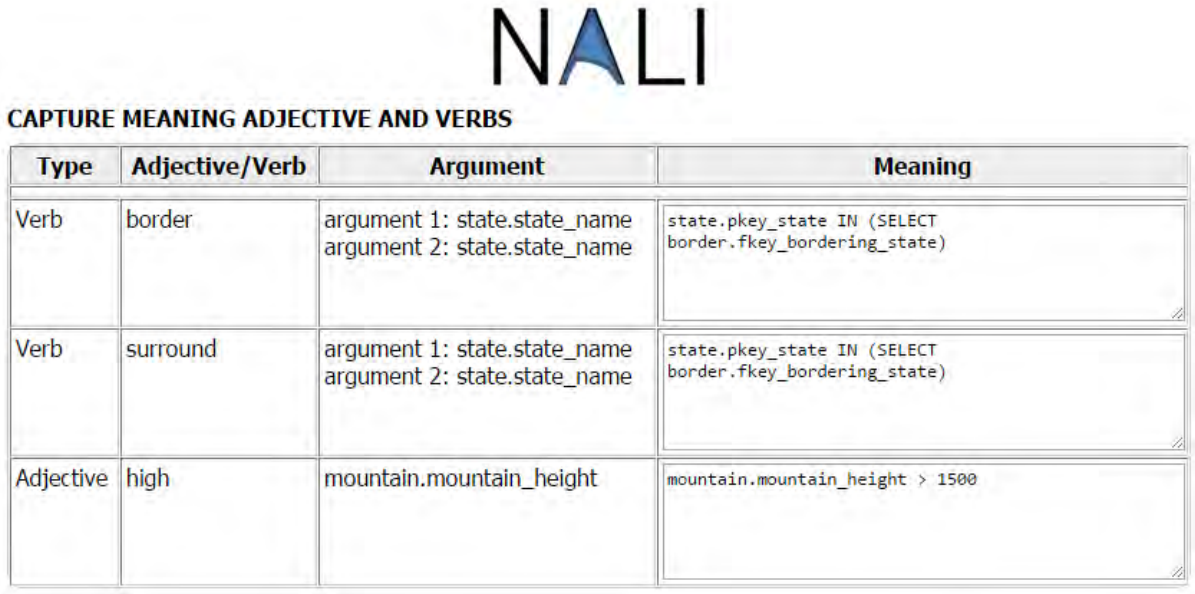


Fig 20 – User interface capturing meaning for adjectives and verbs

```
Function generateNegativeForm(semanticBaseForm)
  If typeOfSQL(semanticBaseForm).equals("EXISTS") Then
    newSemantic = reversePolarityOfExist(semanticBaseForm)
  Else
    newSemantic = reversePolarityOfMainOperator(semanticBaseForm)
  End If
  return newSemantic
End Function
```

Listing 7 – Algorithm generating the SQL conditional expression for the negative form of a verb

The following operations are performed by the sub-routines *reservePolarityOfExits* and *reversePolarityOfMainOperator*:

- reservePolarityOfExits: replaces "EXISTS" by "NOT EXISTS" and vise-versa in the SQL;
- reversePolarityOfMainOperator: negates the comparison operator of the conditional expression in the SQL (i.e. "student.studenMark > 5" becomes "student.studentMark <= 5").

The meaning is auto-generated for adjective superlative forms and included in the configuration. The system selects the record corresponding to either the highest or smallest value (depending on the scalar direction) of the scalar column. Listing 8 presents the algorithm generating the meaning expressed in SQL for the superlative form of adjective.

For the comparative form, the system selects the record where the scale column is greater or lesser (depending on the scale direction being respectively positive or negative) than the scale's column of the subject. For example, the query "Student smarter than John" would correspond to "Select student whose mark is superior to John's mark". Listing 9 presents the algorithm building the semantic for the comparative form of adjective.

```
Function generateSemanticSuperlativeForm(adjective)
  primaryKeyColumn = getPrimaryColumn(adjective.getDescribedColumn().getTable())
  If adjective.scalarDirection = true Then
    semantic = primaryKeyColumn + " IN (SELECT " + primaryKeyColumn + " ORDER BY " +
               adjective. scalarColumn + " DESC LIMIT 1"
  Else
    semantic = primaryKeyColumn + " IN (SELECT " + primaryKeyColumn + " ORDER BY " +
               adjective. scalarColumn + " ASC LIMIT 1"
  End If
 return semantic
End Function
```

Listing 8 – Algorithm generating the SQL conditional expression for the superlative form of an adjective

```
Function generateSemanticComparativeForm(adjective)
  If adjective.scalarDirection = true Then
    Semantic = adjective. scalarColumn + " > (SELECT " + adjective. scalarColumn + " LIMIT 1)"
  Else
    Semantic = adjective. scalarColumn + " < (SELECT " + adjective. scalarColumn + "  LIMIT 1)"
  End If
 return semantic
End Function
```

Listing 9 – Algorithm generating the SQL conditional expression for the comparative form of an adjective

Example: what is the largest city in Wisconsin?

Adjective: large
Superlative form: largest
Comparative form: larger
Scale column: city.city_area
Scale direction: positive

Semantic auto-generated for superlative form: "city.pkey_city IN (SELECT city.pkey_city ORDER BY city.city_area DESC LIMIT 1)"

Semantic auto-generated for comparative form: "city.city_area > (SELECT city.city_area LIMIT 1)"

Final SQL query:

```
SELECT city1.city_name
FROM city AS city1
WHERE city1.pkey_city IN (
  SELECT city2.pkey_city
  FROM city AS city2, state AS state2
  WHERE state2.state_name = 'wisconsin'
    AND city2.fkey_state = state2.pkey_state
  ORDER BY city2.city_area DESC
  LIMIT 1)
```

Note: the condition and clauses included in the final SQL originating from the semantic defined for the superlative form are underlined.

3.4 Design of the bottom-up authoring approach

The bottom-up approach aims to explore the possibility of building a configuration with no human intervention, using the database schema and column synonyms harvested from WordNet as the only sources for customization data.

The first phase of bottom-up extracts the database schema. The schema extraction module leverages JDBC (Java Database Connectivity) which is Java API for database interfacing. The JDBC API also provides a generic interface to read the database meta-data like table's names, column's names, column's types and table's relationships.

The second phase of bottom-up retrieves synonyms for database columns. Each column from the database that is not a primary or foreign key is used to auto-harvest possible synonyms from WordNet. The algorithm describing the construction of bottom-up configuration end-to-end is described in Listing 10.

```
For Each table in DBModel
  For Each column in table
    If NotAPrimaryKey(column) And NotAForeignKey(column) Then
      listSynonyms = getListSynonymsFromWordNet(columnName)
      column.synonyms = listSynonyms
    End If
  End For
End For
```

Listing 10 – Algorithm constructing the configuration automatically through bottom-up approach

The bottom-up approach assumes that the database uses meaningful English nouns for column names; otherwise, no new additional synonyms will be retrieved from WordNet. The WordNet library JWI[5] has been used to interface with WordNet dictionary.

[5] http://projects.csail.mit.edu/jwi/

Chapter 4 Design of the query processing pipeline

The present chapter presents the design of a query interpreter which translates a natural language input query into SQL query using the configuration generated during the system's customization. The first section presents the design objectives and system architecture; the rest of the chapter describes with more details each of the main phases of query processing, namely lexical analysis, syntactic analysis, semantic analysis and SQL Translation.

4.1 Design objective and system architecture

The design objective of the query interpreter is to yield the highest accuracy possible using the configuration model produced during system customization. The configuration includes the following elements:

- the list of nouns mapped to database columns;
- the list of adjectives including the nouns they describe and their corresponding meanings;
- the list of verbs including their arguments and the corresponding meanings.

During query processing, each word's grammatical category needs to be extracted from the natural language query. This task is achieved using a part of speech (POS) tagger and a syntactic parser. The Stanford natural language processing group presents a parser that retrieves grammatical relations between words in a sentence (De Marneffe et al., 2006). The Stanford dependency parser uses a statistical model trained with a corpus of 254,840 English words manually annotated (Silveira et al., 2014). The important effort put into manual annotation addresses the problem of scarcity of gold standard dependency corpus and motivates the use of Stanford parser for this research. The grammatical relations between words from the parse tree facilitate the retrieval of adjectives and verbs along with their arguments. The system's core architecture is, therefore, a syntax-based NLIDB using the Stanford dependency parser.

The processing pipeline translates the natural language query to SQL in four main steps illustrated Fig 21. The lexical analysis phase processes the sentence at word level, the process includes part of speech tagging, lemmatization and named entity recognition. The syntactic analysis leverages the Stanford parser to extract the relationship between words in the sentences. The semantic analysis phase translates the query into an intermediary meaning representation language. In this research, the intermediary query uses first order logic to represent query meaning. Finally, the SQL translation phase converts the logical query into SQL query.

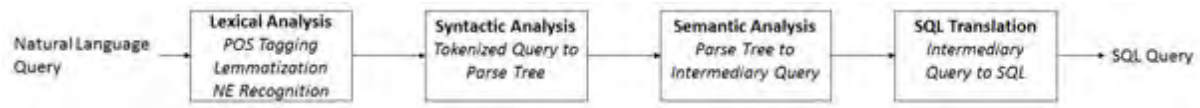


Fig 21 – Processing pipeline from natural language query to SQL

The system architecture is illustrated in Fig 22, it has three conceptual layers which are the client, middleware and persistence layer. The client layer is a Web user interface (see Fig 23) that captures the natural language query and presents the final result to the user. The prototype built is experimental and therefore includes the intermediary results as well. The middleware layer encapsulates the query processing logic which leverages the Stanford NLP API and Java WordNet Interface (JWI). Both the system's backend and external API are built on top of the Java Standard Edition core library. The persistence layer is composed of a relational database management system

where the actual data are stored. The experimental prototype called NALI (NAtural Language Interface) uses a PostgreSQL database but any relational database supporting SQL can be used.

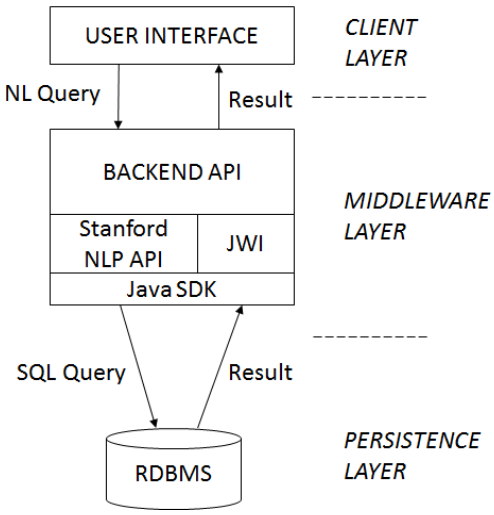


Fig 22 – System's architecture

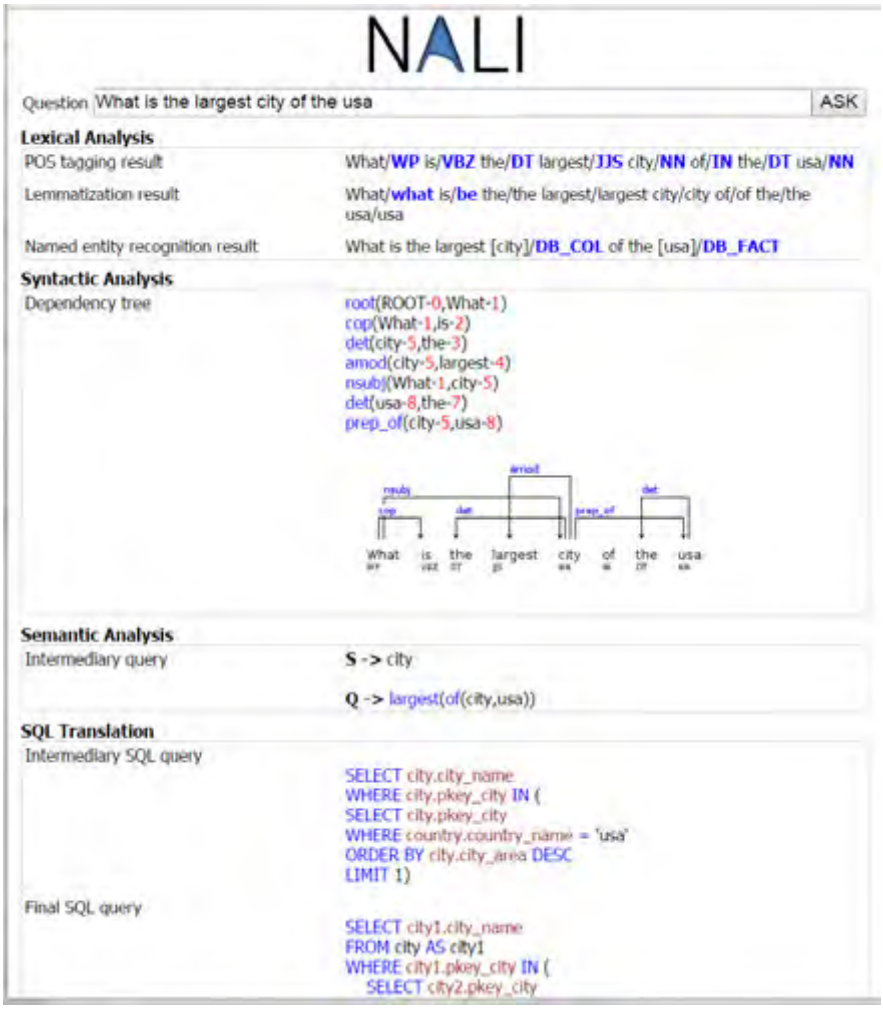


Fig 23 – Processing pipeline user interface

4.2 Lexical analysis

The lexical analysis phase is concerned with processing the sentence at word level, the process includes part of speech tagging, lemmatization and named entity recognition. The subsequent sections present more details for each of the lexical analysis stages.

4.2.1 Part of speech tagging

The part of speech tagging stage associates each word in the text to its corresponding "part of speech" (POS) or grammatical category like nouns, verbs, adjectives, etc. Each grammatical category is represented by a discrete POS tag. POS in this research leverages the open source Stanford POS tagger (Toutanova et al., 2003). The Stanford POS tagger uses the Pen Treebank tag set (Marcus et al., 1993) to encode each grammatical category and is provided with a trained empirical model. The internal model is based on a Conditional Markov Model (CMM) trained with Penn Treebank annotated corpus and yields a 97,24% accuracy score (Toutanova et al., 2003). The tagger is distributed as Java library[6] including the trained model. The POS tagger produces a tokenized query which is a collection of token objects (see Fig 24). Each token is composed of the original word and the tag representing the grammar category.

Example of POS tagging:
Query: what is the longest river in mississippi ?
POS Tokenized Query: what/**WP** is/**VBZ** the/**DT** longest/**JJS** river/**NN** in/**IN** mississippi/**NNS** ?/.

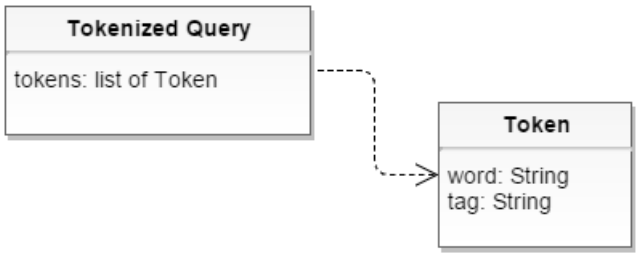


Fig 24 – Structure of a token

4.2.2 Lemmatization

The phase of lemmatization aims to remove ineffectual endings and keep only the base or dictionary form of each word called a "lemma". For example, a plural noun will be transformed to its singular form and a conjugated verb is transformed to the base form. The use of lemma allows more flexibility during semantic analysis like identifying concepts appearing in plural form for example.

Example: which rivers run through states bordering new mexico ?
Lemmatized Query: which river run through state border new mexico ?

The processing pipeline uses the Stanford lemmatizer; it is distributed along with the core API and uses a pre-trained model to perform lemmatization.

4.2.3 Named entity recognition

The named entity recognition (NER) phase labels words from the text that belong to special categories like person's name, location or organization's name. In this research, NER is performed to

[6] The Stanford POS Tagger is distributed under GNU License and accessible on http://nlp.stanford.edu/software/tagger.shtml

mark database columns and facts appearing in the natural language query. The named entities are formatted using IOB (Inside-Outside-Beginning) tags which are standards in NLP field (Ramshaw & Marcus, 1995). The structure of each named entity is represented in Fig 25.

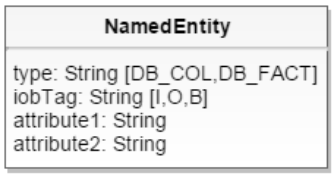


Fig 25 – Structure of named entities

The named entity (NE) type can be either "DB_COL" or "DB_FACT" depending on the NE representing a database column or fact. Attribute1 and attribute2 store respectively the table's name and column's name. The NER module adds a NE tag to each token of the tokenized query. The field *iobTag* store the tag's symbol which can have the following values:

- O: Outside, meaning the current token is not a named entity;
- B: Beginning, meaning the current token is part of a named entity and represents the first word constituting the NE;
- I: Inside, meaning the current token is part of a named entity and represents a word within the NE.

Example: which students enrolled in computer science ?
NER result: which/**O** students/**B** enrolled/**O** in/**O** computer/**B** science/**I** ?/**O**

In the above query, "student" and "computer science" are named entities; "student" and "computer" receives respectively the symbol "B" for being the first word of the NE; and "science" receives the symbol "I" for being within a NE with more than one word. The rest of the words which are not named entities receives a "O" symbol.

Listing 11 presents the algorithm marking database facts and column synonyms found in the text as named entities. The database schema is automatically extracted and the database column's synonyms are populated during system's customization. The interface "getAllDBColumns" retrieves a list with all the columns. The system retrieves and stores database facts from all the columns containing text values in a list accessed through the interface "getAllDBFacts". More than one named entity can be assigned to a token because both database facts and columns can contain duplicated values. For example "area" can be a synonym to both cityArea and stateArea columns; and "New York" is a fact existing in both cityName and stateName columns. A token with more than one named entity requires disambiguation which is presented in the next section.

```
For Each fact in dbModel.getAllDBFacts()
        If (query.contains(fact.word))
                markNE(fact.word,query,"DB_FACT",fact.tableName,fact.columnName)
        End If
End For
For Each col in dbModel.getAllDBColumns()
        If (query.getLemmatizedQuery().contains(col.getSynonyms()))
                markNE(fact.word,query,"DB_COL",col.tableName,col.columnName)
        End If
End For
```

Listing 11 – Named entity recognition algorithm

4.2.3.1 Resolution of ambiguities in named entities

Let X be a word from the natural language query and NE(X) the set of possible named entities associated to X. X is ambiguous when #NE(X) > 1. Three heuristic rules allow resolving lexical ambiguities; one for database fact ambiguities and two for database column ambiguities. The heuristic rules for named entities disambiguation (and for the other modules involving rules as well) were derived from observing examples of both the input (ambiguous named entity, for example) and output (correct named entity, for example). This observation allowed noticing the most occurring common patterns which were codified as rules.

Rule 1 – database fact disambiguation

The first rule is applied when the ambiguous word is an adjective. Formally, rule 1 is applied when there exists an ambiguous word X for which the following conditions are met:

- the attribute "type" for all NE(X) = "DB_FACT";
- there exists in the typed dependency query a triple amod(JJ*,NN*) where X.tag = "JJ*" and Y.tag = "NN*".

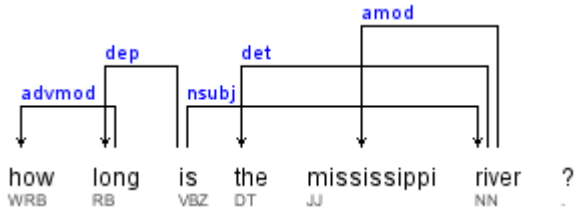
Note:

- amod: is the adverbial modifier relationship which links an adjective (JJ*) to a noun it defines (NN*);
- Y: is the noun defined by the adjective X;
- JJ*: is a part of speech tag starting with JJ which represents an adjective;
- NN*: is a part of speech tag starting with NN which represents a noun.

The engine resolves the ambiguity by selecting the table's name mapped to the noun that the ambiguous adjective describes. Formally, the engine keeps NE(X) where NE(X).attribute1 = NE(Y).attribute1. Note: attribute1 represents the database table associated to the named entity.

Example: how long is the mississippi river ?

Typed dependency query:



In the above example "mississippi" is ambiguous and associated to the two following named entities:

- NE1: type = "DB_FACT", iobTag="B", attribute1 = "state", attribute2 = "stateName"
- NE2: type = "DB_FACT", iobTag="B", attribute1 = "river", attribute2 = "riverName"

The matching triple is: amod(mississippi,river) where:

- NE(river): type = "DB_COL", iobTag = "B", attribute1 = "river", attribute2 = "riverName"

Therefore, the engine resolves the ambiguity by keeping only NE2 for NE(mississippi).

Rule 2 – database column disambiguation

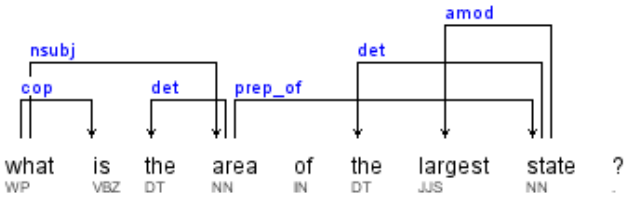
The second rule uses the object of the proposition referring the ambiguous noun to disambiguate. Formally, rule 2 is applied when there exists an ambiguous word X for which the following conditions are met:

- the attribute "type" for all NE(X) = "DB_COL";
- there exists in the typed dependency query a triple prep_*(NN*,NN*) where X.tag = "NN*" (X can correspond to either the first or second argument) and Y.tag = "NN*".

The engine resolves the ambiguity by selecting the table's name mapped to the noun that is the object of the preposition. Formally, the engine keeps NE(X) where NE(X).attribute1 = NE(Y).attribute1.

Example: what is the area of the largest state ?

Typed dependency query:



In the above example "area" is ambiguous and associated to the two following named entities:

- NE1: type = "DB_COL", iobTag="B", attribute1 = "state", attribute2 = "stateArea"
- NE2: type = "DB_COL", iobTag="B", attribute1 = "city", attribute2 = "cityArea"

The matching pattern is: prep_of(area,state) where:

- NE(state): type = "DB_COL", iobTag = "B", attribute1 = "state", attribute2 = "stateName"

Therefore, the engine resolves the ambiguity by keeping only NE1 for NE(area).

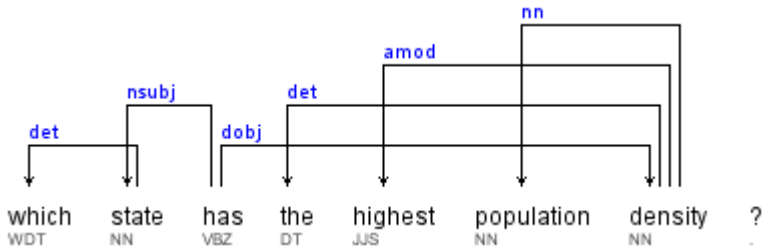
Rule 3 – database column disambiguation

The third rule is applied when the ambiguous word is a verb's object; the corresponding subject is used to disambiguate. Formally, rule 3 is applied when there exists an ambiguous word X for which the following conditions are met:

- the attribute "type" for all NE(X) = "DB_COL";
- there exists in the typed dependency query two triples t1 = nsubj(VB*,NN*) and t2 = dobj(VB*,NN*) where X.tag = "NN*" from t2 and Y.tag = "NN*" from t1.

The engine resolves the ambiguity by selecting the table's name mapped to the verb's subject. Formally, the engine keeps NE(X) where NE(X).attribute1 = NE(Y).attribute1.

Example: which state has the highest population density ?
Typed dependency query:



In the above example “population" is ambiguous and associated to the two following named entities:

- NE1: type = “DB_COL”, iobTag=”B”, attribute1 = “state”, attribute2 = “statePopulation”
- NE2: type = “DB_COL”, iobTag=”B”, attribute1 = “city”, attribute2 = “cityPopulation”

The matching triples are t1 = nsubj (has,state) and t2 = dobj(has,density) where:

- NE(state): type = “DB_COL”, iobTag = “B”, attribute1 = “state”, attribute2 = “stateName”

Therefore, the engine resolves the ambiguity by keeping only NE1 for NE(population).

4.3 Syntactic analysis

The syntactic phase analyses the grammar structure of the natural language sentence. It leverages the Stanford probabilistic context-free grammar parser (Klein & Manning, 2003) which includes an empirical model constructed from manually parsed sentences. The Stanford parser extracts the grammatical relations which are represented as Stanford typed dependencies (SD), a format designed to be “easily understood and effectively used by people who want to extract textual relations” (De Marneffe & Manning, 2008). The SD format represents each grammatical relation as triple composed of the relation’s name, a governor (or head) and a dependant. The head and dependant are words from the sentence while the relation describes the grammatical link between the governor and dependant. A more detailed description of the SD format and exhaustive list of relationships supported can be found in (De Marneffe & Manning, 2008). The ensemble of relationships forms a graph, starting from an abstract ROOT node which is a virtual node added by the parser and representing the entry point to navigate the parsed query’s graph.

Example: John loves Marie
The typed dependency query (illustrated in Fig 26) comprises the following triples:

root(ROOT,loves)
nsubj(loves,John)
dobj(loves,Marie)

Fig 26 – Visualization of the typed dependency query for “John loves Marie”

4.4 Semantic analysis

The phase of semantic analysis extracts and expresses the sentence meaning in an intermediary Meaning Representation Language (MRL). The intermediary query is expressed as a first-order logic (FOL) expression using only the function’s part of FOL. The intermediary query is composed of two parts which are both expressed in FOL: the select and query part (see examples in Table 6). The

select part designates the information that needs to be retrieved and returned in the final result. The query part expresses the restriction or conditions the final result needs to satisfy. The select part must satisfy either one of the two following conditions:

- must be a function of valence 0: if X is this function, the column to be selected corresponds to attribute2 of NE(X);
- must be a unary function: the function name can be either an aggregation term ("count", "sum", "avg", "max" and "min") or an adjective. An adjective indicates the engine to return the scalar column corresponding to the adjective.

Table 6 – Example of query and their corresponding intermediary queries

Natural Language Query	Intermediary query	
	Select part	Query part
what is the area of the largest state ?	area()	of(area,largest(state))
how many rivers are in colorado ?	count(rivers)	be in(rivers,colorado)

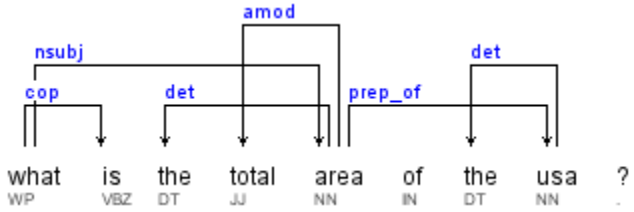
4.4.1 Heuristic rules to build the select part of the intermediary query

The semantic analyser is based on a set of generic heuristic rules that translates the typed dependency query from the parser into an intermediary query for both the select and query parts. The algorithm retrieving the select part uses five heuristic rules to construct the select clause from the typed dependency query. Each rule is composed of a pattern and an associated template. The pattern part is matched against triples from the typed dependency query and the template part describes how the select part is constructed from the matching triples. The patterns and their corresponding templates are presented in Table 7. Each rule is applied following the order in the table below until a matching pattern is found.

Table 7 – List of rules to retrieve the select part of the logical query

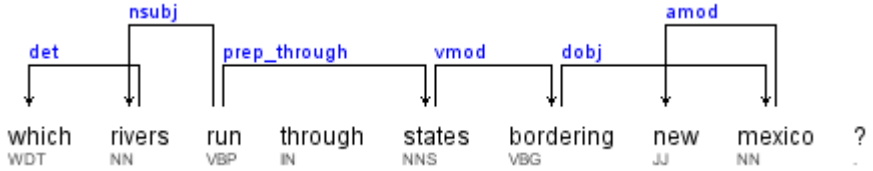
Rule	Pattern looked up	Template	Comment
1	*(NN*,"total") or *(NN*,"average") or *(NN*,"maximum") or *(NN*,"minimum")	sum(NN*) or avg(NN*) or max(NN*) or min(NN*)	Searches for a noun referencing respectively "total", "average", "maximum" and "minimum" to construct an aggregation function with the matched noun as argument
2	*(W*,NN*) or *(NN*, W*)	NN*()	Searches for a Wh- question (tag starting with "W") that is related to a noun (tag starting with "NN"). The latter becomes the select part.
3	*("many","how") and *(NN*, "many")	count(NN*)	Searches for "how many" and selects the noun linked to "many" to build a select part with a count function.
4	*(*,"how")	[*]([first_noun])	When "how" is found, the word it points to becomes the function; and the function argument corresponds to the first noun found in the query
5	-	NN*()	When the first three patterns do not match, the engine selects the first noun found in the query as the select

Example 1: what is the total **area** of the usa ?
Typed dependency query:



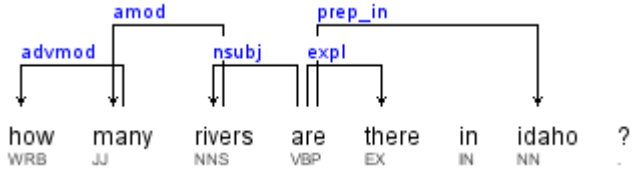
Rule 1 applied, matched pattern: amod(area,total).
Result: sum(area)

Example 2: which **rivers** run through states bordering new mexico ?
Typed dependency query:



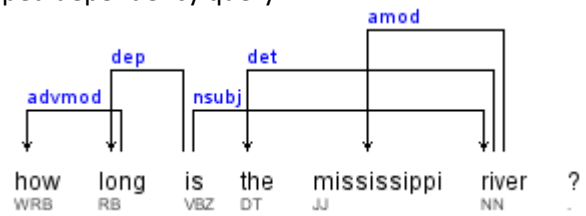
Rule 2 applied, matched pattern: det(rivers,which).
Result: rivers()

Example 3: how many rivers are there in idaho ?
Typed dependency query:



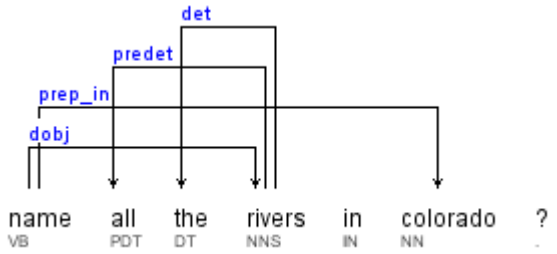
Rule 3 applied, matched patterns: advmod(many,how) and amod(rivers,many)
Result: count(rivers)

Example 4: how long is the mississippi river ?
Typed dependency query:



Rule 4 applied, matched pattern: advmod(long,how) and the first noun is “river”
Result: long(river)

Example 5: name all the rivers in colorado ?
Typed dependency query:



Rule 5 applied, no matching pattern and first noun is “rivers”
Result: rivers()

4.4.2 Construction of the query part of the intermediary query

The construction of the query part is completed in three steps. The first step traverses the typed dependency query from the root element and creates groups of triples read in the same round. The second step constructs the intermediary query corresponding to each group from the first step. The last step merges all intermediary queries and constructs the final intermediary query. The next sections describe in detail the three steps.

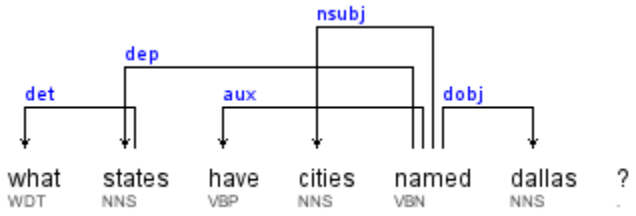
4.4.2.1 Grouping of typed dependency triples

The grouping algorithm is presented in Listing 12. The algorithm starts the traversal of the typed dependency query from the ROOT triple which forms the first group. The second round reads all the triples starting from the dependent element of the ROOT triple to form the second group. The process repeats for each new triple traversed until the entire query is navigated as illustrated in the example. The algorithm produces a two-dimensional array where the first dimension contains the groups and the second the triples within each group.

```
Function groupTripleDependencyQuery()
        DepTriple trip = parsedQuery.getRootTriple()
        Token firstToken = trip.getArgument1()
        browse(firstToken)
End Function

Function browse(Token token)
        DepTriple [] trips = getTripleStartingFrom(token)
        finalListTriples.add(trips)
        For Each DepTriple trip in trips
                browse(trip.getArgument1())
        End For
End Function
```

Listing 12 – Algorithm grouping triples from the typed dependency query

Example: what states have cities named dallas?
Typed dependency query:



List of triples:

det(states-2,what-1)
dep(named-5,states-2)
aux(named-5,have-3)
nsubj(named-5,cities-4)
root(ROOT-0,named-5)
dobj(named-5,dallas-6)

Round 1: browse all the triples starting from ROOT-0
Group 1 created: root(ROOT-0,named-5)

Round 2: browse all the triples starting from named-5
Group 2 created:
dep(named-5,states-2)
aux(named-5,have-3)
nsubj(named-5,cities-4)
dobj(named-5,dallas-6)

Round 3: browse all the triples starting from states-2
Group 3 created : det(states-2,what-1)

Round 4: browse all the triples starting from what-1
Not triple found

Round 5: browse all the triples starting from have-3
Not triple found

Round 6: browse all the triples starting from cities-4
Not triple found

Round 7: browse all the triples starting from dallas-6
Not triple found

The final list of groups created for the above example is presented in Table 8.

Table 8 – Final list of triple groups corresponding to the query: "what states have cities named dallas ?'

Group 1	root(ROOT-0,named-5)
Group 2	dep(named-5,states-2) aux(named-5,have-3) nsubj(named-5,cities-4) dobj(named-5,dallas-6)
Group 3	det(states-2,what-1)

4.4.2.2 Construction of intermediary queries

The second step constructs an intermediary query for each group of triple from step 1. The algorithm for step 2 is presented in Listing 13; it reads each group and calls the rule engine which translates the triples from the group into an intermediary query. The rule engine maps triple patterns to an intermediary query template. The list of rules is presented in Table 9.

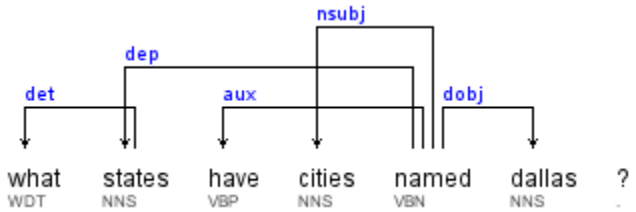
```
For Each tripleGroup in  listOfGroups
        IntermediaryQuery  intQuery = rule(1, tripleGroup) // 1 represents the rule's number

        For (i=2,i <= 6;i++)
                If (intQuery =null)
                        intQuery = rule(i, tripleGroup) // i represents the rule's number
                Else
                        listOfIntQuery.add(intQuery)
                        continue
                End If
        End For
End For
```

Listing 13 – Algorithm that constructs intermediary queries

Table 9 – List of rules used to generate logical queries

Rule	Pattern	Intermediary query template	Type of query
1	nsubj(VB*,NN*) and dobj(VB*, NN*)	VB* (NN*, NN*)	Binary function
2	*(VB*,NN*)	NN*()	Term
3	*(NN*,JJ*)	JJ* (NN*)	Unary function
4	*(JJ*,RBS)	RBS(JJ*)	Unary function
5	prep_*(NN*, NN*)	pre_*(NN*, NN*)	Binary function
6	*(*, NN*)	NN*()	Term

Example: what states have cities named dallas ?
Typed dependency query:



Groups created:

- Group 1: root(ROOT-0,named-5)
- Group 2: dep(named-5,states-2), aux(named-5,have-3), nsubj(named-5,cities-4) and dobj(named-5,dallas-6)
- Group 3: det(states-2,what-1)

Round 1: group browsed: root(ROOT-0,named-5)
Rule applied: no rule
Action: no action

Example continued

Round 2 : group browsed: dep(named-5,states-2), aux(named-5,have-3),nsubj(named-5,cities-4), dobj(named-5,dallas-6)
Rule applied: Rule 1
Pattern "nsubj(VB*,NN*[1])" matched to "subj(named-5,cities-4)"
Pattern "dobj(VB*, NN*[2])" matched to "dobj(named-5,dallas-6)"
Action: create intermediary query with pattern: VB* (NN*[1], NN*[2]);
Result: named(cities,dallas)

Round 3 : group browsed: det(states-2,what-1)
Rule applied: none

The final list of intermediary queries has one element: named(cities,dallas)

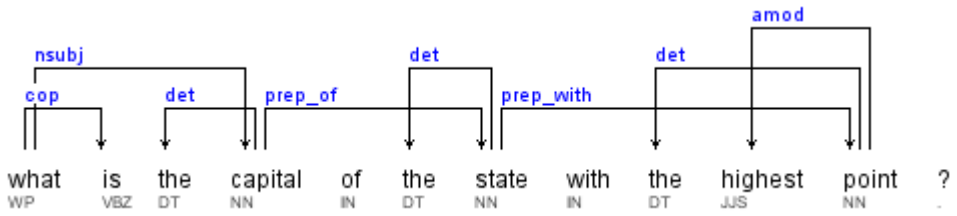
4.4.2.3 Merging of intermediary queries parts into the final query

The merging algorithm is presented in Listing 14; it merges intermediary queries from the previous step two by two starting from the two last queries in the list. The algorithm has six merging rules containing the merge logic presented in Listing 15.

```
Function mergeIntermediarylQuery(IntermediaryQuery[] elements)
        If (elements.length == 1)
                return elements[0]
        End If

        rootElement = elements[elements.length-1]

        For(i=elements.length-2;i>=0;i--)
                rootElement = merge(elements[i],rootElement)
        End For
End Function
```

Listing 14 – Algorithm merging intermediary queries element

Example: what is the capital of the state with the highest point ?
Typed dependency query:



List of intermediary queries (from step 2): "capital", "of(capital,state)", "with(state,point)" and "highest(point)"
Merge round 1: *merge "with(state,point)" and "highest(point)"*
Merging rule 4 applied, result: "with(state,highest(point))"

Merge round 2: *merge "of(capital,state)" and "with(state,highest(point))"*
Merging rule 6 applied, result: "of(capital, with (state,highest(point)))"

Merge round 3: *merge of "capital" and "of(capital, with (state,highest(point)))"*
Merging rule 1 applied, final result: "of(capital, with(state,highest(point)))"

```
Function merge(LogicalQueryElement query1, LogicalQueryElement query2)
If (query1 is Term) // merging rule 1
        If (query2.contains(query1))
                return query2
        End If
End If
If (query1 is unary function And query2 is term) // merging rule 2
        query1.setArgument1(query2)
End If
If (query1 is unary function And query2 is binary function) // merging rule 3
        If (query1.functionName() = query2.functionName())
                return query2
        Else If (query2.contains(query1))
                return query2
        Else If (query2.contains(query1.getArgument1())
                query1.setArgument1(query2)
                return query1
        End If
End If
If (query1 is binary function And query2 is unary function) // merging rule 4
        If(query2.contains(query1.getArgument1())
                Query1.setArgument1(query2)
                return query1
        Else If (query2.getArgument1().contains(query1.getArgument2())
                Query1.setArgument2(query2)
                return query1
        End If
End If

If (query1 is unary function And query2 is unary function) // merging rule 5
        If(query2. getArgument1().contains(query1.getArgument1())
                Query1.setArgument1(query2)
                return query1
        Else If (query2.contains(query1.getArgument1())
                Query1.setArgument1(query2)
                return query1
        Else If (query1.contains(query2.getArgument1())
                Query2.setArgument1(query1)
                return query2
        End If

If (query1 is binary function And query2 is binary function) // merging rule 6
        If (query2.contains(query1.getArgument1()))
                Query1.setArgument1(query2)
                return query1
        Else If (query2.contains(query1.getArgument2())
                Query1.setArgument2(query2)
                return query1
        End If
End If
```

Listing 15 – Merging rules for two intermediary queries

4.5 SQL Translation

The last phase translates the intermediary query into a SQL query. The translation process is executed in two steps: the first step translates the intermediary query into an intermediary SQL query which does not include the FROM clause and joins between tables. The second phase completes the FROM clause, the joins and adds aliases for table in order to avoid naming conflicts.

4.5.1 Construction of the intermediary SQL query

The algorithm translating the Intermediary query to SQL is presented in Listing 16. The algorithm generates an empty SQL before calling the routines processing the select and query part of the intermediary query. The routine processSelectPart contains the logic that inserts the correct column into the select clause of the current SQL from the select part of the intermediary query. The routine *browse* navigates the query part of the intermediary query; for each function or term read, the appropriate processing is called (processBinaryFunction, processUnaryFunction or processTerm). A recursive call of browse routine for each function allows the process to repeat itself until the entire intermediary query is navigated. The algorithms in Listing 17, Listing 18 and Listing 19 present the processing of binary function, unary function, and term respectively.

```
Function translateIntermediaryQuery(IntermediaryQuery intQuery)

        SQLQuery query = new SQLQuery()
        query = processSelectPart(intQuery.getSelectPart())
        query = browse(query, intQuery)

End Function

Function processSelectPart(SQLQuery query, IntermediaryQuery selectPart)

        If (selectPart is Term)
                DBColumn col = selectPart.retrieveColumn()
                query.addSelectClause(col)
                return query
        Else If (selectPart is BinaryFunction)

                If (selectPart.getFunctionName() = “count”)
                        DBColumn col = selectPart.retrieveColumn()
                        col.setAggregation(COUNT)
                        query.addSelectClause(col)
                        return query
                Else
                        Adjective adj = selectPart.retrieveAdjective()
                        DBColumn col = adj.getScalarColumn()
                        query.addSelectClause(col)
                        return query
                End If
        End If
End Function
```

Listing 16 continued

```
Function browse(SQLQuery query, IntermediaryQuery intQuery)
        If (intQuery is BinaryFunction)
                newSQLQuery = processBinaryFunction(sqlQuery, intQuery)
                browse(newSQLQuery, intQuery.getArgument1())
                browse(newSQLQuery, intQuery.getArgument2())
        Else If (intQuery is UnaryFunction)
                newSQLQuery = processUnaryFunction(sqlQuery, intQuery)
        Else
                processTerm(sqlQuery, intQuery)
        End If
End Function
```

Listing 16 – Algorithm translating the intermediary query to intermediary SQL

```
Function processBinaryFunction(SQLQuery sqlQuery, IntermediaryQuery intQuery)
        DBColumn column1 = retrieveDBColumn(intQuery.getArgument1())
        DBColumn column2 = retrieveDBColumn(intQuery.getArgument2())
        Semantic semantic  =
           KnowledgeModel.retrieveVerbSemantic(intQuery.getFunctionName,column1,column2)
        SQLQuery sqlSemantic = semantic.translateToSQL()
        For (whereClause wc in sqlSemantic.getWhereClauses())
                sqlQuery.addWhereClause(wc)
        End For

        If(sqlSemantic.isSubQuery())
                return sqlSemantic.getSubQuery()
        Else
                return sqlQuery
        End If
End Function
```

Listing 17 – Algorithm processing binary functions

```
Function processUnaryFunction(SQLQuery sqlQuery, IntermediaryQuery intQuery)
        DBColumn column = retrieveDBColumn(intQuery.getArgument1())
        Semantic semantic  =
                KnowledgeModel.retrieveAdjectiveSemantic(intQuery.getFunctionName,column)
        SQLQuery sqlSemantic = semantic.translateToSQL()
        For(whereClause wc in sqlSemantic.getWhereClauses())
                sqlQuery. addWhereClause (wc)
        End For
        If(sqlSemantic.isSubQuery())
                return sqlSemantic.getSubQuery()
        Else
                return sqlQuery
        End If
End Function
```

Listing 18 – Algorithm processing unary functions

```
Function processSimpleTerm(SQLQuery sqlQuery, IntermediaryQuery intQuery)
        Value = logQuery.getValue()
        DBColumn column = retrieveDBColumn(intQuery)
        whereClauseExpression = column + ComparisonOp.EQUAL + value
        sqlQuery.whereClause().addWhereClause(whereClauseExpression)
End Function
```

Listing 19 – Algorithm processing term

Example: which state borders kentucky ?

Intermediary query:
select part: state()
query part: border(state,kentucky)

Processing select part of the logical query
The token "state" has a named entity of type *database column* that reads "state.state_name"; which is directly inserted into the main select clause of the intermediary query.
Current intermediary query: SELECT state.state_name

Processing the query part of the logical query
Round 1: browse border(state,kentucky)
Apply Binary Processing: corresponding semantic rule found:
border(state.state_name,state.state_name) -> state.pkey_state IN (SELECT border.fkey_bordering_state)
The semantic part of the rule corresponds to the condition to include inside the current intermediary query.

New intermediary query: SELECT state.state_name WHERE state.pkey_state IN (SELECT border.fkey_bordering_state).

Note: the rule has included a new sub-query, meaning all sub-sequent browsing will include restriction at the level of the sub-query.

Arguments for next browse: state, kentucky

Round 2: browse state
Apply Term Processing: capital is not a database fact (no db NE tag here); therefore, no further action taken.

Round 3: browse kentucky
Apply Term Processing: kentucky is bound to database fact (there is named entity associated to it).
Action: include the restriction: state.state_name = 'kentucky' into the sub-query.

Final Intermediary SQL query:

```
SELECT state.state_name
WHERE state.pkey_state IN (
SELECT border.fkey_bordering_state
WHERE state.state_name = 'kentucky')
```

4.5.2 Construction of the final SQL query

4.5.2.1 Join clause generation

Fig 27 describes the steps in the algorithm of join construction module. The schema of the database and the intermediary SQL query constitute the inputs to build the joins.

Step 1 builds an undirected graph from the database schema where nodes represent tables and links represent relationships between tables (see the algorithm in Listing 20). Fig 28 shows an example of a database schema and its corresponding graph. All the tables in the database are included in the graph. The approach used to produce joins from graphs is similar to (Meng & Chu, 1999).

Step 2 retrieves the list of tables to be joined from the intermediary SQL query. The corresponding algorithm extracts all tables existing in the intermediary query; it is presented in Listing 21.

Step 3 evaluates the paths between all node pairs from the node set corresponding to the tables to be joined. The Dijkstra shortest path algorithm presented in (Dijkstra, 1959) is used to compute the paths.

Step 4 generates the joins between tables from the paths between node pairs. The corresponding algorithm is presented in Listing 22.

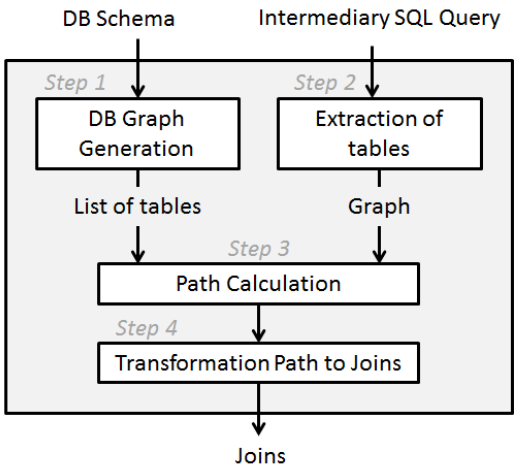


Fig 27 – Steps in join construction

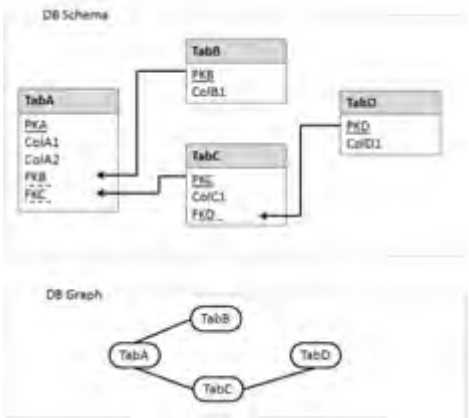


Fig 28 – Construction of a database graph from a database schema

```
Function generateGraph(DBModel dbModel)
        Graph graph = new Graph()

        For Each Table table in dbModel
                Node node1 = new Node(table.getName())
                graph.addNode(node1)

                For Each Column column in table.getColumns()
                        If (column.isForeignKey())
                                Table foreignTable = column.getForeignTable()
                                Node node2 = new Node(foreignTable.getName())
                                If (graph.notContain(node2)
                                        graph.addNode(node2)
                                End If
                                        Edge edge = new Edge(node1,node2)
                                        graph.addEdge(edge)
                        End If
                End For
        End For

        return graph

End Function
```

Listing 20 – Algorithm generating a graph from a database schema

```
Function retrieveListTablesFromIntermediaryQuery(SQLQuery intQuery)
        List listTable = new List()
        browseQuery(listTable, intQuery)
End Function

Function browseQuery(List listTable, SQLQuery intQuery)
        For Each Table table in intQuery.getSelectClause()
                listTable.addUniqueValue(table)
        End For

        For Each WhereClause wc in intQuery.getWhereClause()
                If (wc.hasSubQuery())
                        browse(listTable, wc.getSubQuery())
                Else
                        Table table = wc.getOperand1().getTable()
                        listTable.addUniqueValue(table)
                End If
        End For
End Function
```

Listing 21 – Algorithm retrieving the list of tables to be joined

```
Function generateJoinFromPath(List listNodesInPath)
        List joins = new List()
        For (i = 0; i<listNodeInPath.size()-2;i++)
                Table table1 = dbModel.getTable(listNodesInPath.get(i).getName())
                Table table2 = dbModel.getTable(listNodesInPath.get(i+1).getName())
                If (table1.hasForeignKeyTo(table2))
                        Column localColumn = table1.retrieveLocalColumnTo(table2)
                        Column foreignColumn = table2.retrieveLocalColumnTo(table1)
                        Join join = new Join(localColumn,foreignColumn)
                        listJoins.add(join)
                Else
                        Column localColumn = table2.retrieveLocalColumnTo(table1)
                        Column foreignColumn = table1.retrieveLocalColumnTo(table2)
                        Join join = new Join(localColumn,foreignColumn)
                        listJoins.add(join)
                End If
        End For
        return joins
End Function
```

Listing 22 – Algorithm generating the joins from the paths between nodes representing table to join

4.5.2.2 FROM clause generation

The FROM clause is a comma separated list of all the tables in the SQL query. The tables to include in the FROM clause are extracted from all the other parts of SQL query, and included with no redundancy in the FROM clause. The algorithm generating the FROM clause is presented Listing 23 (the browseQuery routine is defined in Listing 21).

```
Function generateFromClause(SQLQuery intQuery)
        List listTable = new List()
        browseQuery(listTable, intQuery)
        For Each table in listTable
                intQuery.addFrom(table)
        End For
End Function
```

Listing 23 – Algorithm generating the FROM clause

4.5.2.3 Table aliases

The aliases are table synonyms that avoid naming conflicts between the main and sub-queries. Each table is given an alias composed of the original table's name and an index corresponding the level of sub-query nesting (the main query has index 1). The algorithm associating aliases to tables is presented in Listing 24.

The resulting query after the aliases are completed correspond to the final SQL that is sent to the RDBMS to retrieve the result.

```
Function associateAliase(SQLQuery intQuery)
        associateAliase (1, intQuery)
End Function

Function associateAliase(int index, SQLQuery intQuery)
        For Each Table table in intQuery.getFromClause()
                table.addAliase(table.getName()+index)
        End For
        For Each WhereClause wc in intQuery.getWhereClause()
                If (wc.hasSubQuery())
                        associateAliase (index+1, wc.getSubQuery())
                End If
        End For
End Function
```

Listing 24 – Algorithm associating aliases to table's names

Chapter 5 Experiment design

A NLIDB prototype called NALI has been developed; it implements the design introduced in chapters 3 and 4. This chapter presents the design of the experiments listed below:

1) The first experiment evaluates the top-down approach; it assesses the top-down capability to reduce the workload for customization and the system's accuracy when provided a configuration for only terms harvested from an unannotated training corpus.

2) The second experiment evaluates the bottom-up approach; it assesses the accuracy yielded from a model with no manual customization and helps evaluate the usefulness of this approach.

3) The third experiment evaluates the processing pipeline and allows analysing the cases where the system did not provide the correct answers and study the sources of errors.

4) Finally, we compare the performance obtained with NALI to other similar NLIDB

The remainder of the chapter describes the material and design of the above experiments.

5.1 Material and experiment design

The experiments are based on testing the system prototype NALI with a corpus of natural language questions and a relational database. The geo-query database and query corpus have been selected to evaluate the system (Tang & Mooney, 2001). The following reasons motivated the choice of geo-query:

- the questions from geo-query corpus have rich grammatical structures with a high degree of logical complexity (Pazos et al., 2013) and will allow assessing the system's coverage;
- geo-query is the most used corpus in the NLIDB literature; this facilitates comparing the result to other systems.

The concise version of the corpus (250 queries) has been selected because it contains very few duplications of questions with the same grammar structure. The resources provided along with the corpus include a list of questions[7], the structure, and content of a Prolog database containing the facts to answer the questions, and the logical queries written in Prolog that answer the questions.

We constructed a relational database version of geo-query and populated with data from the Prolog database facts. The Entity-Relationship model of the geo-query database is shown in Fig 29 and the database schema is shown in Fig 30.

[7] The country's name has been streamlined throughout the corpus to read "USA"

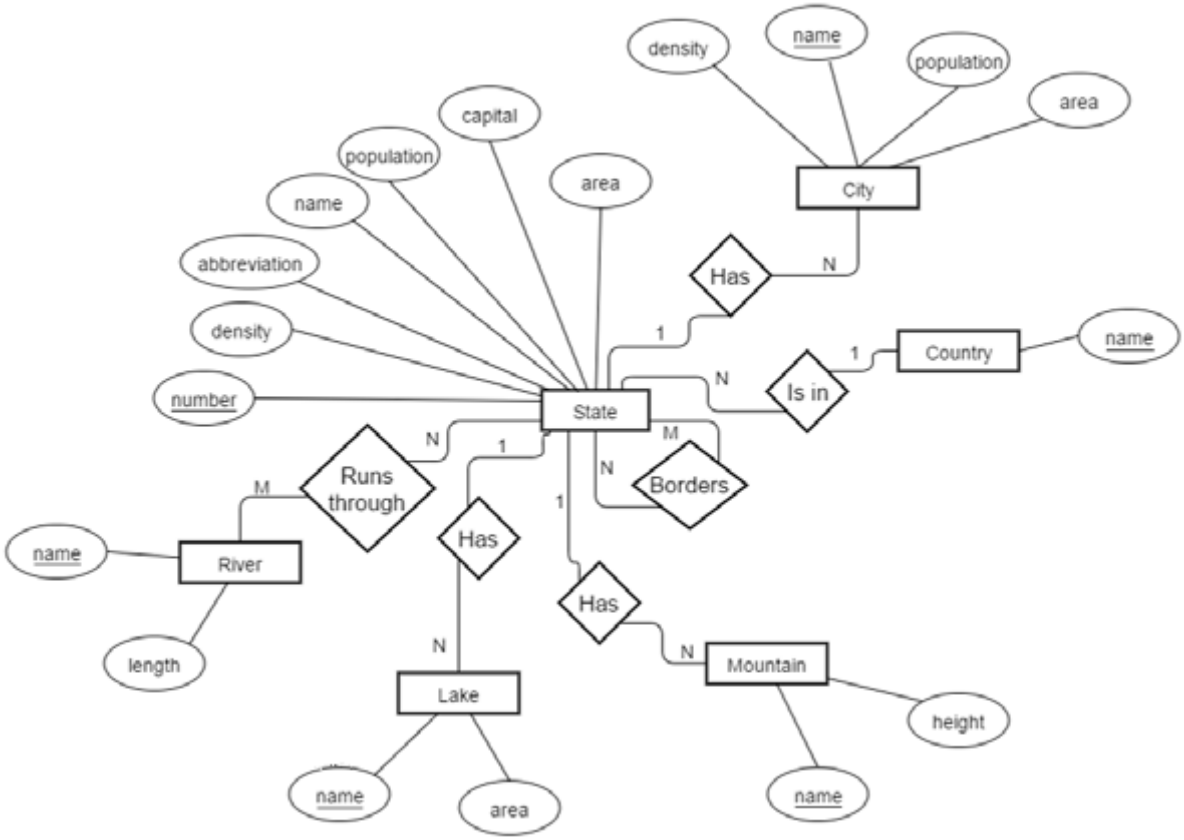


Fig 29 – Entity-relationship model of geo-query

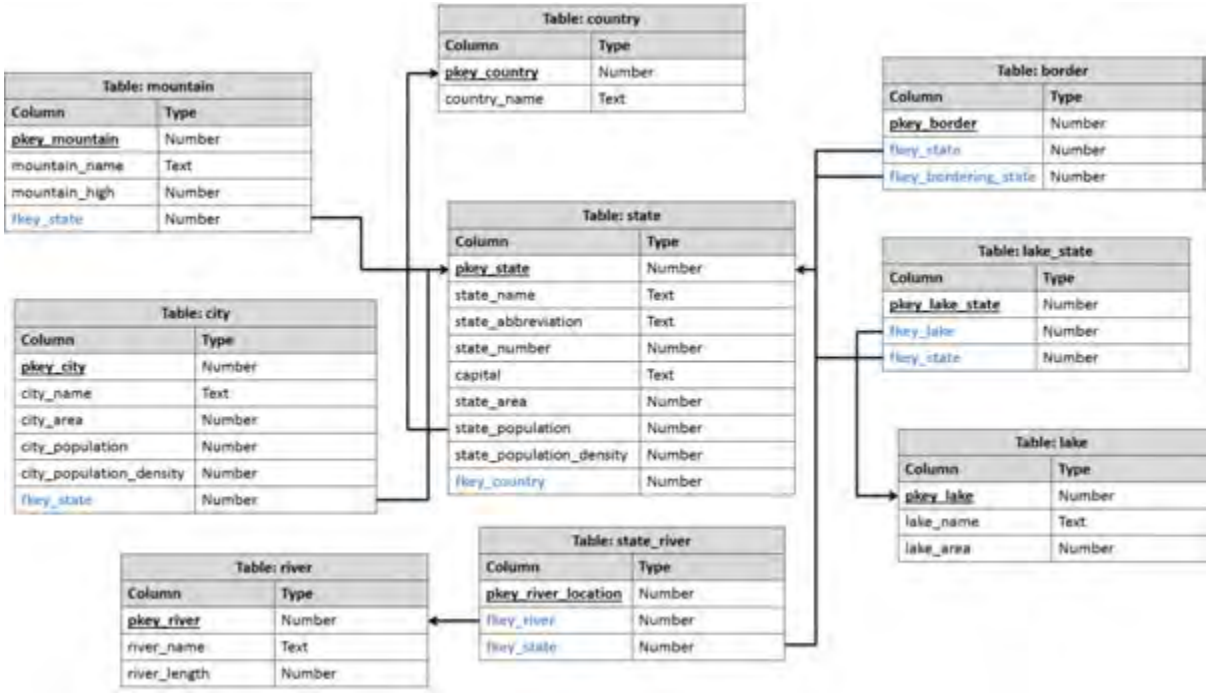


Table: country

Column	Type
pkey_country	Number
country_name	Text

Table: mountain

Column	Type
pkey_mountain	Number
mountain_name	Text
mountain_high	Number
fkey_state	Number

Table: border

Column	Type
pkey_border	Number
fkey_state	Number
fkey_bordering_state	Number

Table: state

Column	Type
pkey_state	Number
state_name	Text
state_abbreviation	Text
state_number	Number
capital	Text
state_area	Number
state_population	Number
state_population_density	Number
fkey_country	Number

Table: lake_state

Column	Type
pkey_lake_state	Number
fkey_lake	Number
fkey_state	Number

Table: city

Column	Type
pkey_city	Number
city_name	Text
city_area	Number
city_population	Number
city_population_density	Number
fkey_state	Number

Table: lake

Column	Type
pkey_lake	Number
lake_name	Text
lake_area	Number

Table: river

Column	Type
pkey_river	Number
river_name	Text
river_length	Number

Table: state_river

Column	Type
pkey_river_location	Number
fkey_river	Number
fkey_state	Number

Fig 30 – Structure of a relational database version of geo-query

The metrics used to assess the system's performance are precision and recall defined as follow (Manning et al., 2008):

$$Precision = \frac{\#(relevant\ items\ retrieved)}{\#(retrieved\ items)} = \frac{\#true\ positive}{\#true\ positive + \#false\ positive}$$

$$Recall = \frac{\#(relevant\ items\ retrieved)}{\#(relevant\ items)} = \frac{\#true\ positive}{\#true\ positive + \#false\ negative}$$

Most of NLIDB in the literature reviewed uses a different definition of recall (referred to as Recall" here), which reads:

$$Recall'' = \frac{\#(retrieved\ items)}{\#(relevant\ items)} = \frac{true\ positive + false\ positive}{true\ positive + false\ negative}$$

In order the compare the result, the recall for systems using a different definition has been recalculated and streamlined to the standard definition.

$$Recall = Recall'' \times Precision = \frac{\cancel{\#true\ positive + false\ positive}}{\#true\ positive + false\ negative} \times \frac{\#true\ positive}{\cancel{\#true\ positive + \#false\ positive}}$$

$$Recall = \frac{\#true\ positive}{\#true\ positive + \#false\ negative}$$

A list of correct SQL (gold SQL result) has been manually created in order to automate the evaluation of the metrics. The remainder describes the design of experiments, the questions they answer, the test set up and the result format.

5.2 Experiment 1 – evaluation of the top-down approach

The first experiment addresses to the following question:

1) Does the exploitation of an unannotated corpus of sample questions combined with automatic generation of configuration for negative form of verbs, comparative and superlative form of adjective reduce the workload required to customize a NLIDB? If yes, to what extent?

In order to evaluate the effectiveness of the top-down approach, the administrator customizing the system is simulated using the following assumptions:

- the administrator has the knowledge of both the database structure and the domain;
- the administrator knows SQL and can therefore express meaning as a SQL conditional expression;
- the administrator is capable of providing the correct mappings and meanings for the terms harvested.

The above assumptions allow developing an automated test where the system's administrator is emulated. The virtual administrator includes the correct mapping and semantics only for the terms harvested. The experiment will help find the accuracy yielded when using a configuration model with only the terms harvested through top-down are mapped.

The top-down approach assumes the existence of a corpus of unannotated questions prior configuration. This requirement is emulated by splitting the corpus into two disjoint parts: a training set used for term harvesting and a testing set. The model resulting from the configuration is tested against the questions in the testing set. Different proportions between the training and testing set

are used to evaluate top-down. Each proportion corresponds to a specific experiment, Table 10 lists all the experiments along with their respective sizes of the training and testing set.

Table 10 – proportions of the training and testing set used for evaluation

Experiment	Size of training set	Size of testing set
Experiment A	100	150
Experiment B	125	125
Experiment C	150	100
Experiment D	175	75
Experiment E	200	50
Experiment F	225	25

Using several ratios for the training and testing set will allow determining if and how each proportion affects the final accuracy. The content of both the training and testing set is selected randomly from the main corpus while ensuring that no query appear simultaneously in both sets. For each experiment, 10 different samples of both the training and testing set are randomly selected to run each experiment. The following actions are performed for each experiment:

- 10 samples of both the training and testing set are randomly generated according to the proportion set for the experiment;
- the top-down module is used to automatically harvest terms from the training sample;
- the emulated virtual administrator adds mapping and semantics for only the terms harvested to produce a configuration model;
- the authoring system includes automatically semantics for negative form of verbs, comparative and superlative form of adjectives;
- the configuration model produced is used by the processing pipeline to answer the questions in the testing set;
- the gold SQL result table is used to automatically calculate the precision and recall;
- the evaluation module counts the number of manual[8] and automatic entries in the configuration model.

The result collected will help assess the accuracy of the configuration model produced through top-down under multiple settings. The experiments will also show how many manual entries are required for respectively noun mapping, adjective updates, and semantics mapping in order to weight the workload required for customization. The number of automatic mapping entries can be compared to manual ones in order to assess how the system does contribute toward reducing the workload. Each result table is aggregated to produce the average metrics by experiment and the global average for all the experiments will correspond to the final metrics for the top-down method.

5.3 Experiment 2 – evaluation of the bottom-up approach

The second experiment addresses the following questions:

2) How effective is the use of the database schema to build a configuration model with no manual customization?

[8] Manual in this context refers to the entries provided by the emulated administrator

3) To what extent do additional synonyms from WordNet contribute toward improving the final accuracy of bottom-up?

In order to evaluate the bottom-up approach, a configuration model is automatically generated using the database schema and WordNet as the only sources of data. The automated testing for bottom-up includes the following steps:

- the bottom-up configuration model is generated from both the database schema and WordNet;
- the configuration model is used in the processing pipeline to answer all the 250 questions in the corpus;
- the gold SQL result table is used to automatically calculate the precision and recall.

The final result includes the configuration model and the metrics' values. The experiment results will provide insights on firstly the accuracy of the bottom-up approach and secondly on how the use of an off-the-shelf lexicon does contribute toward improving accuracy.

5.4 Experiment 3 – Evaluation of the processing pipeline

The third experiment addresses the following questions:

4) How effective is the processing pipeline?
5) What are the limits of the processing pipeline components?

The experiment 3 reviews the effectiveness of the processing pipeline. To assess the processing pipeline, a "perfect" top-down configuration model is trained using the entire corpus. This configuration should ideally yield a 100% recall and is therefore used to get insights on the limits of the processing pipeline. Each incorrect query is manually reviewed to examine at which phase of processing the error originated from and what caused the fail. The experiment result will provide insights on the performance at each stage in the processing pipeline.

5.5 Experiment 4 – comparison of the result to other systems

The forth experiment addresses the following question:

6) How does NALI perform compared to both NLIDB with similar design objectives and systems with a different design?

The results from the top-down approach are compared to other NLIDB systems evaluated with geo-query. The NLIDBs selected for comparisons are split into two groups. The first group called "Group A" contains the systems whose design objectives are similar to the top-down approach and satisfy the two following conditions. The first criterion is that the system should be customizable by an administrator with only basic knowledge of database systems (including knowledge of SQL) and the domain; no background in computational linguistics should be required. The second condition is that no manual annotation of a query corpus should be required to customize the system as this implies an important workload. The systems not satisfying one of the two conditions are included in the second group called "Group B". Table 11 gives the list of systems the top-down model is compared to, their group and a short comment motivating their classification.

The literature review showed a trade-off between portability and accuracy; systems with a complex configuration module achieve greater accuracy compared to more portable ones. The result will help

to get insights on how the top-down approach performs comparatively to firstly other portable systems with similar design objectives from Group A and secondly less portable systems from Group B. The metric used for comparison is recall because it gives the proportion of correct answers respective to relevant items. The recall for systems using definition 1 is recalculated using the standard definition.

Table 11 – List of systems the top-down result is compared to

NLIDB	Group	Type of data source	Comment
PANTO (Wang et al., 2007)	Group A	Ontology	Acquires the lexicon automatically from WordNet
FREYA (Damljanovic et al., 2010)	Group A	Ontology	Builds the configuration from an interactive dialog with the user in natural language
Prototype in (Goldwasser et al, 2011)	Group A	Knowledge Base	Uses an unannotated corpus and unsupervised method to construct a model
Prototype in (Giordani & Moschitti, 2012)	Group A	RDB	Uses the database meta-data to build the configuration
Prototype in (Chandra, 2006)	Group B	RDB	Requires to first manually annotate a training corpus with their corresponding valid SQL
COCKTAIL prototype 1 (Tang & Mooney, 2001)	Group B	Knowledge Base	Requires to first manually annotate a training corpus with their corresponding meaning expressed in first order logic
COCKTAIL Prototype 2	Group B	Knowledge Base	
COCKTAIL Prototype 3	Group B	Knowledge Base	
COCKTAIL Prototype 4	Group B	Knowledge Base	
COCKTAIL Prototype 5	Group B	Knowledge Base	
PRECISE (Popescu et al., 2003)	Group B	RDB	Prototype customized at design time; no authoring system provided
GINSENG (Bernstein et al., 2005)	Group B	Knowledge Base	Required testers with a background in both databases and computational linguistics to customize the system
KRISP (Kate & Mooney, 2006)	Group B	Knowledge Base	Requires to first manually annotate a training corpus with their corresponding meaning expressed in the system's custom meaning representation language
Prototype in (Minock et al., 2008)	Group B	RDB	Background in computational linguistics required to customize the system
Prototype in (Giordani & Moschitti, 2010)	Group B	RDB	Requires to first manually annotate a training corpus with their corresponding syntactic parse tree

Chapter 6 Experiment results and discussion

This chapter presents and discusses the experimental results.

6.1 Experimental results

6.1.1 Result evaluation of the top-down approach

Table 12 presents the average precision and recall for all the top-down experiments; Table 13 shows the average number of emulated manual entries and automatic entries in the configuration model. The detailed[9] results for each experiment are presented in Appendix A. The experiments with a greater training set yielded a relatively better precision and recall. This result shows that increasing the size of the corpus of sample queries will have a positive impact on the final accuracy.

Table 12 – Average precision and recall for each experiment

Experiment	Precision	Recall
Experiment A	75.5	72.9
Experiment B	76.2	73.2
Experiment C	76.8	74.8
Experiment D	78.6	75.8
Experiment E	79.8	76.2
Experiment F	77.2	74.0
Average	**77.4**	**74.5**

Table 13 – Average number of manual and automatic configuration entries

Experiment	#noun manually mapped	#adjective manually updated	#semantics manually mapped	#semantics auto mapped
Experiment A	16.0	7.4	2.6	31.0
Experiment B	16.5	7.9	2.8	34.1
Experiment C	17.5	7.8	2.9	38.2
Experiment D	18.1	8.0	3.4	40.3
Experiment E	19.6	8.0	3.5	42.5
Experiment F	19.5	8.0	3.7	45.2
Average	**17.9**	**7.9**	**3.2**	**38.6**

The configuration model produced through top-down contained in average 68 entries with the break down below:

1) 18 manual mapping between noun and database columns;
2) 8 manual completion of adjective information;
3) 3 manual completion of semantics;
4) 39 automatic mapping of semantics.

[9] The complete experiment details including the parsing result of each query, the configuration models and the training sets can be accessed from: http://people.cs.uct.ac.za/~tmvumbi/nali_experiments.html The queries incorrectly answered are highlighted with a red background.

The emulated administrator performed 29 manual entries in average out of which 18 mappings between noun and database columns, 8 completion of adjective information and 3 inclusion of semantics. The mapping of noun and completion of adjective information are straightforward tasks and represented 90% of the manual entries. Providing semantics requires writing the restriction in SQL and constitutes a relatively tougher task. In total 42 semantic entries are included in the model out of which 39 are automatically provided by the engine. The automatic semantics corresponds to negative form of verbs, comparative and superlative form of adjectives. The experiment shows that the top-down approach has automated 93% of semantic generation which corresponds to the hard work for customization.

The top-down model has been used by the processing pipeline to respond to questions from the testing set. The average metrics obtained are respectively 77.4 % precision and 74.5 % recall. These results are put in context and compared to other NLIDBs in 6.1.4.

6.1.2 Result evaluation of the bottom-up approach

The configuration model auto-constructed with the bottom-up approach only includes mapping between columns and their synonyms. The column's synonyms have been retrieved from either the database schema or WordNet. The processing pipeline using the configuration model constructed through the bottom-up approach has attempted to respond to 241 questions from the 250 in the dataset and answered correctly 80 questions. The metrics obtained are respectively 33.2% precision and 32.0% recall. Table 14 presents the mappings automatically built and the source of each synonym[10].

The first source of incorrect parsing is the insufficient number of mapping entries between nouns and database columns. The bottom-up model contained 38 mappings between nouns and database columns out of which 14 (37%) are synonyms retrieved from WordNet. None of the synonyms from WordNet were found in the questions in geo-query and consequently their inclusion in the model did not improve the final accuracy. Table 15 gives the list of missing synonyms and their corresponding database columns.

The second source of incorrect parsing is the absence of manual update of adjective information which allows indicating the scalar direction and column for each adjective. Because the scalar column and direction are not present, the engine cannot automatically generate the semantics for comparative and superlative form of adjective which affects negatively the final accuracy. The fact there is no manual configuration of semantics for adjectives and verbs also reduces the accuracy. Finally, the engine cannot automatically generate the semantics for the negative form of verbs since the semantics for the base forms are not present; this reduces further the accuracy.

The questions that were correctly answered by the bottom-up model are basic retrieval queries not involving nesting. The corpus contains 105 such basic questions out of which 80 are answered correctly, which is 76%.

[10] More details including the parsing result for each query is accessible at the following address: http://people.cs.uct.ac.za/~tmvumbi/nali_experiments.html. The queries incorrectly answered are highlighted with a red background.

Table 14 – List of terms produced by bottom-up model (the external terms from WordNet are highlighted)

Synonym	DB Column	Source
city	city.city_name	Schema
metropolis	city.city_name	WordNet
urban_center	city.city_name	WordNet
population	city.city_population	Schema
area	city.city_area	Schema
country	city.city_area	Schema
density	city.city_density	Schema
denseness	city.city_density	WordNet
state	country.country_name	Schema
nation	country.country_name	WordNet
country	country.country_name	Schema
land	country.country_name	WordNet
commonwealth	country.country_name	WordNet
res_publica	country.country_name	WordNet
body_politic	country.country_name	WordNet
lake	lake.lake_name	Schema
area	lake.lake_area	Schema
country	lake.lake_area	Schema
mountain	mountain.mountain_name	Schema
mount	mountain.mountain_name	WordNet
height	mountain.mountain_height	Schema
tallness	mountain.mountain_height	WordNet
river	river.river_name	Schema
length	river.river_length	Schema
road	road.road_number	Schema
route	road.road_number	WordNet
state	state.state_name	Schema
province	state.state_name	Schema
abbreviation	state.state_abbreviation	Schema
population	state.state_population	Schema
area	state.state_area	Schema
country	state.state_area	Schema
number	state.state_number	Schema
figure	state.state_number	WordNet
density	state.state_density	Schema
denseness	state.state_density	WordNet
capital	state.capital	Schema
working_capital	state.capital	WordNet

Table 15 – List of column's synonyms missing in the bottom-up model

Noun	DB Column
point	mountain.mountain_name
people	city.city_population
elevation	mountain.mountain_height
citizen	city.city_population
spot	mountain.mountain_name
peak	mountain.mountain_name
people	state.state_population
citizen	state.state_population

6.1.3 Result evaluation of the processing pipeline

The top-down model trained with the entire corpus yielded 85.5% precision and 82.4% recall. 44 queries were not answered correctly due to errors from the lexical parser (43 %), semantic analysis (30 %) and SQL translator (27 %). The prototype attempted answering 241 questions out of which 206 are correct answers. Table 16 shows the number and proportion of errors originated from each stage of the processing pipeline.

Table 16 – Sources of errors in the processing pipeline

Phase	Module	Number of errors	Percentage
Lexical analysis	Part of speech tagging	12	27 %
	Named entity disambiguation	7	16 %
Semantic analysis	Intermediary query construction	13	30 %
SQL Translation	SQL Construction	12	27 %
Total		44	

In the lexical analysis module, the incorrect queries have originated from either an incorrect part of speech (POS) tagging or incorrect disambiguation of named entities. The POS tagger did not classify correctly 12 requests representing 27 % of errors observed and 5% of the entire corpus. All the errors observed in POS are due to firstly the noun "states" incorrectly classified as the verb "to state" in the third person singular and secondly the verb "border" incorrectly classified as a noun. The example bellow illustrates a typical case of POS incorrect classification.

Query: "What states border montana ?"
Incorrect classification: "what/WP states/VBZ border/NN montana/NN ?/."
Correct classification: "what/WP states/NN border/VB montana/NN ?/."

The incorrect POS errors originate from the Stanford POS tagger privileging a grammatically possible but semantically improbable interpretation of the query that can be rewritten as "The border of montana states what?". The Stanford POS tagger selects the most probable classification using a trained statistical model which achieves a high accuracy (95 % with geo-query) yet not perfect. The error cases like the above are progressively reduced as the statistical model is improved.

The engine allows more than one named entity to be associated to a word. A simple rule based disambiguation strategy has been used to resolve ambiguities. In total 98 ambiguous cases have been found and the rule-based algorithm correctly disambiguated 91 cases representing 93 %. The 7 failed cases are due to the lack of suitable rule to disambiguate.

The semantic parser has been fed with the correct tokenized query from lexical analysis 219 cases (88%) and produced the correct intermediary query in 206 cases achieving a precision of 94%. The semantic analysis phase produced 13 incorrect results due to non-existing rules as well.

The SQL translator module received the correct intermediary query in 217 cases (87%) and produced the correct SQL for 205 queries which corresponds to a precision of 94%. The SQL translator failed to produce the correct SQL 12 times due to not supported English constructions. The unsupported queries involved mainly the use of a custom *GROUP BY* clause like in "What is the largest state capital in population" and query requiring a comparison with an aggregated value like in "Which state borders most states".

6.1.4 Result comparison with other systems

Table 17 and Table 18 presents the results from NLDB in Group A and Group B.

Table 17 – Result of NLIDB from Group A

NLIDB	Type of data source	Corpus / Size	Precision	Recall
PANTO (Wang et al., 2007)	Ontology	Geo-query/880	88.1	**75.6**
FREYA (Damljanovic et al., 2010)	Ontology	Geo-query/250	81.2	**65.9**
Prototype in (Giordani & Moschitti, 2012)	RDBMS	Geo-query/800	81.0	**71.2**
Prototype in (Goldwasser et al, 2011)	Knowledge Base	Geo-Query/250	-	**65.6**
NALI (top-down model)	RDBMS	Geo-query/250	77.4	**74.5**

Group A contains 4 portable NLIDBs with design objectives similar to the top-down approach, out of which one system that targets a relational database is like in this research. The top-down recall (74.5 %) is higher than the system targeting RDB which is 71.2% (Giordani & Moschitti, 2012). PANTO (Wang et al., 2007) achieves a slightly better recall (75.6%) and it targets ontology. The remaining system in group A are FREYA which targets ontologies as well and achieves 65.9% recall and (Goldwasser et al, 2011) which achieves 65.6% recall.

The second group includes systems with an authoring approach requiring either more expertise or more workload to customize which translates to potentially better performances. The top-down result outperforms 8 of the 11 systems from group B. The system scoring the highest performance is GINSENG with a reported 91.3% recall over an ontology version of geo-query (Bernstein et al., 2005). The work targeting RDB from group B that performed better than the top-down model are respectively PRECISE (Popescu et al., 2003) with 77.5% recall and the prototype in (Minock et al., 2008) with 75.7% recall.

Table 18 – Result of NLIDB from Group B

NLIDB	Data source	Corpus / size	Precision	Recall
Prototype in (Chandra, 2006)	RDBMS	Geo-query/250	96.0	**67.2**[11]
COCKTAIL prototype 1 (Tang & Mooney, 2001)	Knowledge base	Geo-query/1000	89.9	**71.4**
COCKTAIL Prototype 2 (Tang & Mooney, 2001)	Knowledge base	Geo-query/1000	89.0	**66.8**
COCKTAIL Prototype 3 (Tang & Mooney, 2001)	Knowledge base	Geo-query/1000	91.4	**64.7**
COCKTAIL Prototype 4 (Tang & Mooney, 2001)	Knowledge base	Geo-query/1000	90.8	**64.5**
COCKTAIL Prototype 5 (Tang & Mooney, 2001)	Knowledge base	Geo-query/1000	87.1	**58.8**
PRECISE (Popescu et al., 2003)	RDBMS	Geo-query/880	100	**77.5**
GINSENG (Bernstein et al., 2005)	Knowledge base	Geo-query/880	92.8	**91.3**
KRISP (Kate & Mooney, 2006)	Knowledge base	Geo-query/250	90.5	**67.4**
Prototype in (Minock et al., 2008)	RDBMS	Geo-query/250	86.0	**75.7**
Prototype in (Giordani & Moschitti, 2010)	RDBMS	Geo-query/250	73.6	**66.2**

6.2 Result discussion

We hypothesized that it is feasible to build a portable NLIDB targeting a relational database whose configuration requires only the knowledge of databases and the subject domain without sacrificing the system coverage and accuracy. Four experiments have been conducted in order to respond the research questions. The following sections discuss the result obtained.

6.2.1 Top-down evaluation

The first experiment investigated the effectiveness of the top-down approach and aimed to answer the following question:

1) Does the exploitation of an unannotated corpus of sample questions combined with automatic generation of configuration for negative form of verbs, comparative and superlative form of adjective reduce the workload required to customize a NLIDB? If yes, to what extent?

The experimental result has shown that pre-harvesting the key lexical terms allowed reducing most of the configuration work into a few straightforward mappings between database objects and harvested terms. Only 26 such mappings on average have been required to customize NALI for geo-

[11] The high recall (96%) reported in (Chandra, 2006) is due to the fact that only questions not involving nested queries (175 questions out of 250) have been used to evaluate the recall. The system responded correctly to 168 of the 250 questions in the dataset which corresponds to an actual recall of 67.2% that is used in Table 18 in order to compare fairly the result to other systems.

query. The result has additionally shown that automatic generation of configuration allowed further reducing the workload for customization by auto-generating 93% of the configuration for verb and adjective meaning for geo-query. The result obtained with top-down is put in context and compared to the related work in section 6.2.4.

The top-down approach assumes the pre-existence of a corpus of sample questions which will not always be available at design time. A possible way to address this problem is to construct a minimalistic configuration model (using the bottom-up approach for example) and record the failing questions to be used as sample corpus for top-down. The bottom-up and top-down approaches can, therefore, be used complementarily.

6.2.2 Bottom-up evaluation

The second experiment investigated the effectiveness of the bottom-up model and aimed to answer the following questions:

2) How effective is the use of the database schema to build a configuration model with no manual customization?
3) To what extent do additional synonyms from WordNet contribute toward improving the final accuracy of bottom-up?

The evaluation of bottom-up has shown that this approach yields a smaller recall; with only 32.0% of the questions being answered correctly with geo-query. The low accuracy of bottom-up is due to the relatively small lexicon and the lack of semantics for verbs and adjectives. However, the bottom-up model has been shown to handle relatively well simple queries not involving nesting; 76% of simple questions in geo-query have been correctly answered. Consequently, the bottom-up approach can be used to construct an initial model that will be improved at a later stage.

Concerning question 3, WordNet did not improve the final accuracy of the bottom-up model while testing with geo-query. None of the synonyms retrieved through WordNet (presented in Table 14) were used in the questions. The database schema combined with an off-the-shelf lexicon did not provide sufficient configuration data to yield an acceptable recall. This result suggests that it remains necessary to gather at least some of the configuration entries from a domain's expert to yield an acceptable accuracy for a system targeting a relational database. The result observed with the bottom-up approach is put in context and compared with the related work in section 6.2.4.

The bottom-up result can be improved by using additional information from a meta-database (the database describing the schema) when this is available. This avenue was not exploited in the present research due to time limitation and can be explored as a future work. A research project using the meta-database but without WordNet can be found in (Giordani & Moschitti, 2012).

6.2.3 Processing pipeline evaluation

The third experiment investigated the effectiveness of the processing pipeline and aimed to answer the following questions:

4) How effective is the processing pipeline?
5) What are the limits of the processing pipeline components?

The processing pipeline achieves an overall recall of 74.5% using the top-down configuration. The use of a simplified meaning representation language (only function's part of first order logic) allowed building lightweight components for the processing pipeline based on small number of heuristic

rules. The rule-based modules developed yielded high precision; 93 % for the disambiguation algorithm, 94 % for semantic analysis and 94 % for SQL translator.

Concerning question 5, the main causes of errors in the processing pipeline were the limitation of the POS tagger used and the lack of suitable production rules for the rule based components of the processing pipeline. The POS tagger used is continuously improved and such errors will be minimized with future versions. The generic production rules created at design time were not modified during evaluation in order to avoid a bias on the result by overfitting the prototype to geo-query.

6.2.4 Comparison with other systems

The forth experiment compared the result observed with the top-down and bottom-up approaches to similar systems and aimed to answer the question:

6) How does NALI perform compared to both NLIDB with similar design objectives and systems with a different design?

The top-down approach uses a sample query corpus in order to reduce the customization workload. A similar method is found with empirical approaches where a corpus is used to train a statistical model. Most of the NLIDB systems reviewed in this category use a supervised training approach with an annotated corpus to construct automatically a configuration model. Examples include (Tang & Mooney, 2001), (Kate & Mooney, 2006), (Chandra, 2006) and (Giordani & Moschitti, 2010) which respectively achieve a recall of 71.4%, 67.4%, 67.2% and 66.2%. The use of an annotated corpus allows constructing a relatively more precise configuration model; however, this is done at the expense of portability as manually annotating a corpus is a costly task. The top-down approach uses an unannotated corpus and thus avoids the extra workload due to manual customization. The recall observed with top-down (74.5%) is higher than the empirical based NLIDBs reviewed using an annotated corpus. This result is encouraging given the fact top-down is relatively more portable since it avoids the annotation work. The reviewed NLIDB evaluated with geo-query that uses an unannotated corpus like for the top-down is (Goldwasser et al, 2011). The prototype in (Goldwasser et al, 2011) uses a non-supervised training approach and achieves 65.6% recall, which is comparatively lower than the top-down result.

The top-down approach does not require the user to have a background in computational linguistics and uses SQL to express the meaning during configuration. This choice allows an administrator with knowledge of SQL with no background in computational linguistic to customize the system. However, a system requiring a background in computational linguistics offers a more expressive authoring approach which translates into a broader system coverage. This is shown with the prototypes in (Bernstein et al., 2005), (Popescu et al., 2003) and (Minock et al., 2008) which respectively achieve a recall of 91.3%, 77.5% and 75.7%. These results are higher than recall achieved by both empirical systems and top-down approach.

The bottom-up approach is an attempt to construct a configuration model with no manual configuration using only the database schema and WordNet. A work similar to the bottom-up model is found in (Giordani & Moschitti, 2012) where the prototype additionally includes information inserted by a domain expert in the meta-database but does not use WordNet. The prototype in (Giordani & Moschitti, 2012) targets a relational database like in this research and achieves a recall of 71%. This result shows that additional configuration information from a human expert yields a better accuracy compared to automatically retrieving synonyms from only WordNet when a relational database is targeted. The second related work reviewed similar to bottom-up is found in

(Wang et al., 2007) where the prototype constructs the configuration model from an ontology and WordNet with no additional information from a domain expert; the recall achieved is 75.6%. The result observed with ontology motivated the construction of a model attempting the same approach with a relational database. However, the bottom-up evaluation has shown that this approach, when not provided with additional information from a domain expert like in (Giordani & Moschitti, 2012), does not provide sufficient configuration data to yield an acceptable recall when interfacing a relational database.

Chapter 7 Conclusion

This research set out to investigate how to simplify customization of NLIDB to relational databases. The review of literature (presented in chapter 2) shows a trade-off between portability and coverage with portable systems achieving a relatively smaller coverage and accuracy while approaches ensuring coverage of complex queries require an important effort for customization. The main contribution of the present research is the proposition of customization approaches that reduce the manual workload, therefore, making NLIDBs more portable and easier to adopt. The following sections review the main research contributions and present possible future work.

7.1 Contributions

The first contribution of this work is the top-down approach to customization. The top-down approach constitutes an attempt to address the current gap that exists between portability and coverage. The experimental result for top-down has shown that pre-harvesting key terms from a sample query corpus sensibly reduces the manual workload needed for customization. The reduction factor is further improved by generating automatically the configuration for negative form of verbs, comparative and superlative form of adjectives. The fact the top-down model uses an unannotated corpus of questions allows avoiding the cost due to manual annotation. It is therefore possible for example to use the logs from a NLIDB search history as-is in order to mine for new terms and improve a NLIDB system's accuracy with a relatively little effort. However, closing the gap between portability and coverage is yet an open problem that has not been completely solved with the top-down approach. The top-down approach contributes in reducing this gap especially with relational databases. The result achieved with top-down put in context is higher than similar portable NLIDB reviewed using an annotated or unannotated sample query corpus.

The second contribution of this work is the assessment of a configuration approach (bottom-up) where the configuration model is generated completely automatically using inputs from solely the database schema and WordNet. The evaluation of a prototype implementing bottom-up with geo-query corpus has shown that this approach does not provide sufficient configuration data to yield an acceptable recall. This result suggests that it remains necessary to have at least some of the configuration manually provided to achieve an acceptable accuracy with relational databases. However, the experiment has also shown that the bottom-up model can handle relatively well simple queries not involving nesting. This result is encouraging given the fact no manual configuration has been provided up front and suggests that the bottom-up model can be used at least as a starting point that can be incrementally improved at a later stage.

The third contribution of the present work is the development of NALI, a NLIDB prototype system that translates a natural language query to SQL. The techniques used to implement the prototype are not new but their combination into one system is what makes the work unique. A relational database version of geo-query has been designed to evaluate the prototype system. This database can be reused by other future research projects targeting a relational database which need to be tested with geo-query.

7.2 Future work

The present research focused more on the correctness of the final result and less on the performance of methods developed. Further work can be done to improve the efficiency of methods developed. For example, a further study can investigate the possibility to include a query optimization module to the architecture that removes unnecessary sub-queries which have a negative impact on performance. Including database facts in the dictionary can as well create a performance problem when a large database is interfaced. Further work can be done to investigate the possibility of using relationship between concepts in the intermediary query to decide during runtime which columns to include in the dictionary and avoid importing the entire database.

The geo-query database has meaningful name for entities and their properties which have been used by the bottom-up approach to construct the initial configuration. There is no guarantee however that database objects will have a meaningful name and this will directly impact the accuracy of the bottom-up model. A future research can investigate the possibility of accessing the meta-database (database describing the data structures) when this is available and use it as an additional source of configuration along with the database object names and WordNet.

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Appendix

Appendix A – Result top-down evaluation

Table 19 – Experiment A results

Sample	Precision	Recall	#Nouns manually mapped	#Adjective manually updated	#Semantics manually mapped	#Semantics auto mapped
Experiment A - 1	74.0	70.0	16.0	7.0	3.0	32.0
Experiment A - 2	76.0	74.0	14.0	7.0	3.0	33.0
Experiment A - 3	78.0	75.0	18.0	7.0	1.0	35.0
Experiment A - 4	78.0	76.0	14.0	7.0	3.0	36.0
Experiment A - 5	72.0	70.0	14.0	8.0	2.0	30.0
Experiment A - 6	77.0	74.0	14.0	8.0	3.0	27.0
Experiment A - 7	76.0	72.0	16.0	7.0	3.0	29.0
Experiment A - 8	74.0	71.0	18.0	7.0	3.0	28.0
Experiment A - 9	74.0	72.0	20.0	8.0	3.0	30.0
Experiment A - 10	76.0	75.0	16.0	8.0	2.0	30.0
Average	**75.5**	**72.9**	**16.0**	**7.4**	**2.6**	**31.0**

Table 20 – Experiment B results

Sample	Precision	Recall	#Nouns manually mapped	#Adjective manually updated	#Semantics manually mapped	#Semantics auto mapped
Experiment B - 1	76.0	72.0	18.0	8.0	4.0	36.0
Experiment B - 2	76.0	72.0	16.0	8.0	3.0	34.0
Experiment B - 3	77.0	73.0	15.0	7.0	3.0	30.0
Experiment B - 4	75.0	72.0	14.0	8.0	3.0	34.0
Experiment B - 5	82.0	80.0	19.0	8.0	3.0	34.0
Experiment B - 6	78.0	75.0	15.0	8.0	1.0	36.0
Experiment B - 7	74.0	70.0	17.0	8.0	2.0	32.0
Experiment B - 8	78.0	76.0	18.0	8.0	3.0	35.0
Experiment B - 9	70.0	68.0	17.0	8.0	4.0	33.0
Experiment B - 10	76.0	74.0	16.0	8.0	2.0	37.0
Average	**76.2**	**73.2**	**16.5**	**7.9**	**2.8**	**34.1**

Table 21 – Experiment C results

Sample	Precision	Recall	#Nouns manually mapped	#Adjective manually updated	#Semantics manually mapped	#Semantics auto mapped
Experiment C - 1	77.0	75.0	17.0	8.0	3.0	39.0
Experiment C - 2	76.0	75.0	17.0	8.0	3.0	35.0
Experiment C - 3	78.0	75.0	20.0	7.0	2.0	36.0
Experiment C - 4	74.0	71.0	18.0	7.0	2.0	35.0
Experiment C - 5	76.0	75.0	16.0	8.0	3.0	40.0
Experiment C - 6	75.0	74.0	18.0	8.0	2.0	41.0
Experiment C - 7	82.0	80.0	19.0	8.0	3.0	40.0
Experiment C - 8	76.0	74.0	16.0	8.0	4.0	37.0
Experiment C - 9	81.0	77.0	15.0	8.0	3.0	38.0
Experiment C - 10	73.0	72.0	19.0	8.0	4.0	41.0
Average	**76.8**	**74.8**	**17.5**	**7.8**	**2.9**	**38.2**

Table 22 – Experiment D results

Sample	Precision	Recall	#Nouns manually mapped	#Adjective manually updated	#Semantics manually mapped	#Semantics auto mapped
Experiment D - 1	78.0	76.0	20.0	8.0	4.0	36.0
Experiment D - 2	81.0	78.0	19.0	8.0	3.0	40.0
Experiment D - 3	78.0	73.0	19.0	8.0	4.0	43.0
Experiment D - 4	71.0	68.0	17.0	8.0	3.0	38.0
Experiment D - 5	81.0	77.0	18.0	8.0	4.0	39.0
Experiment D - 6	78.0	76.0	17.0	8.0	3.0	42.0
Experiment D - 7	86.0	85.0	18.0	8.0	3.0	42.0
Experiment D - 8	83.0	80.0	17.0	8.0	3.0	40.0
Experiment D - 9	72.0	69.0	17.0	8.0	3.0	42.0
Experiment D - 10	78.0	76.0	19.0	8.0	4.0	41.0
Average	**78.6**	**75.8**	**18.1**	**8.0**	**3.4**	**40.3**

Table 23 – Experiment E results

Sample	Precision	Recall	#Nouns manually mapped	#Adjective manually updated	#Semantics manually mapped	#Semantics auto mapped
Experiment E - 1	91.0	88.0	20.0	8.0	4.0	44.0
Experiment E - 2	80.0	74.0	18.0	8.0	3.0	42.0
Experiment E - 3	91.0	90.0	20.0	8.0	4.0	43.0
Experiment E - 4	81.0	78.0	20.0	8.0	3.0	42.0
Experiment E - 5	71.0	66.0	19.0	8.0	4.0	41.0
Experiment E - 6	69.0	68.0	20.0	8.0	3.0	39.0
Experiment E - 7	78.0	72.0	19.0	8.0	4.0	44.0
Experiment E - 8	80.0	76.0	20.0	8.0	4.0	45.0
Experiment E - 9	78.0	74.0	20.0	8.0	2.0	43.0
Experiment E - 10	79.0	76.0	20.0	8.0	4.0	42.0
Average	**79.8**	**76.2**	**19.6**	**8.0**	**3.5**	**42.5**

Table 24 – Experiment F results

Sample	Precision	Recall	#Nouns manually mapped	#Adjective manually updated	#Semantics manually mapped	#Semantics auto mapped
Experiment F - 1	75.0	72.0	18.0	8.0	4.0	44.0
Experiment F - 2	91.0	88.0	20.0	8.0	3.0	46.0
Experiment F - 3	86.0	76.0	20.0	8.0	4.0	46.0
Experiment F - 4	88.0	88.0	20.0	8.0	4.0	48.0
Experiment F - 5	62.0	60.0	19.0	8.0	3.0	47.0
Experiment F - 6	56.0	56.0	18.0	8.0	3.0	44.0
Experiment F - 7	70.0	68.0	20.0	8.0	4.0	44.0
Experiment F - 8	75.0	72.0	20.0	8.0	4.0	46.0
Experiment F - 9	82.0	76.0	20.0	8.0	4.0	45.0
Experiment F - 10	87.0	84.0	20.0	8.0	4.0	42.0
Average	**77.2**	**74.0**	**19.5**	**8.0**	**3.7**	**45.2**