PLACE IN GISCIENCE: FROM PLACE DESCRIPTIONS TO LANDMARKS

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ABSTRACT

Place lies at the center of geography’s interests since geography is about place in common knowledge, and is one of the most fundamental concepts in human geography as well as the broad field of the humanities and social sciences. Nowadays, place in GIScience has become a hot topic, moving to the analysis of text-based information such as text messages and web documents. This place knowledge can be revealed in textual place descriptions, which are a common way for people to convey information based on their perception or memory of spatial information. Place descriptions provide a rich source of human spatial knowledge that is complementary to the knowledge found in current space-based GIS.

Place knowledge, however, is qualitative (instead of quantitative), relative in its reference frame (instead of absolute), vernacular (and thus, also arbitrary in granularity and types, in contrast to feature catalogues of authoritative GIS), and more. Large corpora of place descriptions provide this place knowledge different from the geometry-based information stored in current GIS. They can be harvested from the Web, and will allow us to have a better understanding of the spatial knowledge. However, harvesting place descriptions and extracting spatial knowledge contained in the descriptions still remains a significant challenge.

The hypothesis is that it is possible to develop a model that supports a fully automatic procedure towards extracting landmarks from place descriptions in natural language. The hypothesis is tested, using the novel algorithms designed and implemented in this research. There are four main phases, namely: constructing place graphs from place descriptions, harvesting large corpora for generating place graphs, similarity matching for integrating spatial information, and extracting landmarks from web-harvested place descriptions.

First, this research focuses on the implementation of algorithms based on cognitively motivated heuristics, and evaluating the automated process, in order to automatically produce plausible sketch maps from the spatial content of place descriptions. Second, this research proposes a novel approach of harvesting place descriptions related to a particular environment from relevant web pages that include the environment, and extracting spatial information from the descriptions. Third, this research addresses a new approach of resolving ambiguous or synonymous place names from place descriptions by exploring the given relationships with other spatial features. It matches place names from multiple descriptions by developing a
novel labelled graph matching process that relies solely on the com-
parison of string, linguistic, and spatial similarities between identi-
fied places. Last, this research focuses on developing a landmark ex-
traction model from the place graphs produced by applying the ap-
proaches of three phases above, and tests an implementation of the 
proposed model that is fully scalable in spatial coverage as well as
spatial granularity, paving the way towards automated identification
of cognitively salient features as landmarks.

This research contributes towards automatic interpretation of nat-
ural language place descriptions, the integration of spatial informa-
tion extracted from the descriptions, and the improvement of feature
matching methods for dealing with spatial semantics, or in general,
to spatial knowledge extraction from place descriptions. The major
outcome of this research is a model and specification of efficient al-
gorithms to extract landmarks from unstructured place descriptions,
mainly focusing on spatial knowledge from place descriptions in or-
der to identify cognitive landmarks based on the knowledge.
DECLARATION

This is to certify that:

1. the thesis comprises only my original work towards the PhD except where indicated in the Preface,

2. due acknowledgement has been made in the text to all other material used,

3. the thesis is fewer than 100 000 words in length, exclusive of tables, maps, and bibliographies.

Melbourne, November 2016

Junchul Kim
This thesis is based on published works from my PhD research during candidature. The contents such as some ideas, algorithms and figures have appeared previously in the following publications:

**JOURNAL ARTICLES**


J. Kim, M. Vasardani, and S. Winter. Landmark extraction from web-harvested place descriptions. *German Journal on Artificial Intelligence (Künstliche Intelligenz)*, published online, 2016.


**PEER-REVIEWED CONFERENCE ARTICLE**

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LIST OF ALGORITHMS

Algorithm 1  Algorithm of placement decision making process  
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ACRONYMS

Agrep  approximate global regular expression print  
API  application programming interface  
GIR  geographic information retrieval  
GIS  geographic information system  
GIScience  geographic information science  
HTML  hyper text markup language  
LEM  landmark extraction model  
NER  named entity recognition  
NL  natural language  
NLP  natural language processing  
OSM  OpenStreetMap  
PCG  pairwise connected graph  
QSR  qualitative spatial reasoning  
SPG  spatial property graph  
URL  uniform resource locator  
XML  extensible markup language
Place lies at the center of geography’s interests since geography is about place in common knowledge, and is one of the most fundamental concepts in human geography as well as the broad field of the humanities and social sciences (Cresswell, 2014). In the early 1970s, the word ‘place’ was first conceptualized as a meaningful site that combines location, locale, and sense of place from geographers such as Tuan (1977, 1979). They also provided the confirmatory evidence that place plays an integral role in human experience. More experimental perspective of geography has been considered with its notion of a sense of place (e.g. Relph, 1993, 1996). Places can also function as landmarks from a geographic perspective, but are then stripped of their rich internal meaning and instead, linked with a location (Winter and Richter, 2014, p. 15). There are also connections between places and landmarks, since landmarks are spatial references which are used to locate other places in mental spatial representation.

Due to a lot of progress in both web harvesting techniques and natural language processing (NLP) over the years, place in geographic information science (GIScience) has become a hot topic, moving to the analysis of text-based information such as text messages and web documents (Abdelkader et al., 2015; Adams et al., 2015). This place knowledge can be revealed in textual place descriptions, which is a common way for people to convey information based on their perception or memory of spatial information. Place descriptions provide a rich source of human spatial knowledge that is complementary to the knowledge found in current space-based geographic information systems (GISs). In addition, large corpora of place descriptions provide a plethora of human spatial knowledge, different from the geometry-based information stored in current GISs. These place descriptions, reflecting everyday communication, frequently refer to landmarks.

Place knowledge, however, is qualitative (instead of quantitative), relative in its reference frame (instead of absolute), vernacular (and thus, also arbitrary in granularity and types, in contrast to feature catalogues of authoritative GISs), and more. Interestingly, the qualitative spatial relations in place descriptions are often used to generate a place representation such as a sketch map via qualitative spatial reasoning process in the field of spatial cognition. Moreover, place information in natural language (NL) is typically not georeferenced and if taken out of its conversational context, can be highly ambiguous with regards to its localization. This information can represent different perspectives on the same locality as these emerge from different indi-
individual experience and knowledge. Globally, place names are highly ambiguous, and in addition, place descriptions include vernaculars, non-gazetteered synonyms (written ones may also include abbreviations) or refer to places that are not gazetteered at all. Therefore, automatic interpretation of place descriptions still remains a challenge because of these difficulties.

The scientific core of this research is to better understand how place knowledge can be revealed in textual place descriptions and what can be extracted from the place knowledge, and in particular, to support the development of automatic collection and interpretation of place descriptions. This research therefore focuses on addressing efficient approaches of transforming place descriptions to landmarks. The approaches are based on the methods resolving ambiguous or synonymous place names from place descriptions and their relationships. Moreover, this research also suggests a dynamic sketch map drawing algorithm to place representation.

1.1 BACKGROUND AND PROBLEM STATEMENT

Place descriptions contain spatial knowledge that is to a large extent shared and meaningful, thus, allowing for successful human communication. This research refers to the general definition and notion: ‘Places are the conceptual entities that enable cognitive structuring of the spatial aspects of reality’ (Bennett and Agarwal, 2007), and ‘Places are typically determined by entities in the geographic environment or by relations between entities in the environment rather than by externally imposed coordinates and geometric properties’ (Winter and Freksa, 2012). Since people are increasingly reliant on description-based localization in query or dialog-driven geolocation services such as local search, car navigation, emergency assistance or public transport planner services, the challenging task of understanding NL place descriptions become important.

Large corpora of place descriptions provide this spatial knowledge different from the geometry-based information stored in current GISs. The place descriptions reflecting the spatial knowledge can be harvested from the Web, for example, Wikipedia or blogs which are major resources for sharing information of places. However, harvesting place descriptions and extracting spatial knowledge contained in the descriptions still remain a significant challenge. It is because there are no suitable tools that currently exist to automatically harvest place descriptions of a specific environment such as a city, and to automatically interpret them for extracting the knowledge like landmarks considering different (conversational) contexts.

The major challenges that demand more research, therefore, are clearly identified as follows:
Harvesting place descriptions

Place descriptions can be harvested from Web platforms such as Wikipedia, business websites, blogs, and social networks services. However, harvesting place descriptions from the Web demands new approaches to a specific target environment, instead of tedious crowdsourcing of place descriptions (Richter and Winter, 2011). A target environment represents a specific region such as the boundary of a city. In order to generate a place model from large corpora from the Web, the place descriptions need to be related to their target environment. For this purpose, this research proposes a novel approach of harvesting relevant web pages that include place descriptions related to a particular environment.

Unstructured place descriptions

Linguistic researchers have been working on parsers that can process unrestricted language input for spatial content. For example, a conceptual framework had been presented for the tagging and parsing of text to extract movement information (Hornsby and Naicong, 2009). Other work has studied the semantics of locative expressions of various languages (Kracht, 2002; Zlatev, 2007). Based on the latter, a method was proposed to assign reference objects, locata and spatial relations roles to linguistic terms (Kordjamshidi et al., 2010), and a parser was presented extracting spatial features and qualitative spatial relations between them from NL place descriptions (Khan et al., 2013; Liu et al., 2014). To handle the unstructured place descriptions, these parsers need to be considered carefully.

Ambiguous place names and qualitative spatial relations

Place names are highly ambiguous, and place information in NL is typically not georeferenced\(^1\). Thus, traditional toponym resolution — named entity recognition (NER) using gazetteers — can fail in many instances. Furthermore, these places are linked with qualitative spatial relations, with all the vagueness and indeterminacy inherent in NL, which makes a purely geometric analysis of configurations difficult. Thus, matching of place names between multiple descriptions needs to build on the spatial relations.

Qualitative representation

A sketch map based on a place description can provide a window to a human mental representation of a place, since place descrip-

\(^1\) There are exceptions, for example, georeferenced Wikipedia entries.
tions are commonly used to convey spatial information based on human perceptions of places. Sketch maps are, in this context, two-dimensional representations of features in an environment, and their spatial relations. However, in the descriptions, people tend to use qualitative expressions, i.e., qualitative spatial directions such as ‘east’ and qualitative spatial distances such as ‘near’. The qualitative information expressed in a vague manner needs to be interpreted by cognitive heuristics as people apply. However, it still remains a question whether place descriptions with their potentially underspecified or even conflicting information can be automatically translated in a sketch map.

In an additional effort towards better human-machine interaction, this research also focuses on generating sketch maps from the extracted spatial content of unrestricted NL place descriptions, which may include ambiguous or uncertain spatial relations. In many situations, such as emergency response, having a machine-generated sketch from such verbal descriptions could support human decision making (Egenhofer, 1997).

Landmark extraction

Landmarks are cognitively salient spatial objects with significant characteristics for constructing a cognitive map of spaces in terms of prominence, uniqueness, salience, and distinctiveness. The evidence of cognitive significance to landmarks such as roles of references has been supported by previous research, i.e., identifiable objects as external reference points (Lynch, 1960), salient and familiar anchor points (Couclelis et al., 1987), and reference points which help identify the location of other points (Sadalla et al., 1980). Due to these characteristics of landmarks, people prefer to use them in wayfinding process or navigating system. Place descriptions can reveal these landmarks which are broadly used and shared by people.

However, most existing methods rely on spatial databases such as network datasets or digital maps, considering three main categories: visual, structural, and cognitive properties. Spatial databases do not contain human spatial knowledge-based landmarks, despite their use in everyday communication. It is mainly due to lack of information in relation to human spatial knowledge. The landmarks extracted from current spatial databases do not reflect the cognitively salient spatial objects that people often use in their communication. Therefore, an automatic landmark identification technique based on human spatial knowledge should be considered.
1.2 Hypothesis and Research Questions

Considering the problem identified above, this research is firstly concerned with harvesting place descriptions from the Web and extracting spatial information from the descriptions. Secondly, this research investigates place modelling with regards to extracting spatial information from the descriptions, building place models, and integrating place models. Lastly, a model of identifying landmark will be addressed by spatial analysis using spatial features and their spatial relations. Thus, this research addresses the hypothesis:

It is possible to develop a model that supports a fully automatic procedure towards extracting context-based landmarks from a large corpus of place descriptions.

To test this hypothesis, this research identifies a series of questions to be investigated:

- How can we model spatial information extracted from an individual place description and translate a model into a sketch map automatically?
- What kinds of place descriptions can be harvested from the Web? Are they a rich source that reveals human spatial knowledge, in particular, for a specific environment such as a city?
- How can we integrate a large corpus of Web-harvested place descriptions into a knowledge database? Is exploring the given relationships with other spatial features needed to resolve ambiguous or synonymous place names from place descriptions?
- Is it also possible to match highly ambiguous place names from multiple descriptions since the descriptions include vernaculars, abbreviations, non-gazetteered synonyms or places that are not gazetteered at all?
- What properties can be used to identify landmarks from the place knowledge? How can we measure the properties to extract landmarks?
- What is expected in landmarks extracted from different contextual views of place descriptions?

1.3 Research Objectives and Approach

The main objectives of this research are to better understand how people describe places in NL place descriptions, to learn how people externalize their mental representation of a place, and to learn about place knowledge they reveal, such as landmarks by investigating the relations to the locations referred to. To achieve these objectives, this
research consists of the individual parts which aim to interpret place descriptions, to integrate spatial information extracted from them, to address efficient approaches for translating place descriptions into plausible sketch maps, and to extract landmarks from place descriptions which reflect human spatial knowledge. To address the research questions set out in the introduction, this section presents the general overview of the research approach and therein, the connections between the individual parts of this thesis:

- Dynamic Sketch map drawing strategy,
- Harvesting large corpora of place descriptions,
- Similarity matching for integrating spatial information,
- Landmark extraction model from place descriptions.

The overall workflow of this thesis is shown in Figure 1. For this research purposes, two different data sources are considered. One is a set of surveyed place descriptions of the University of Melbourne’s Parkville campus to address the way of generating sketch maps, reflecting human mental representation of a place. The other one is a large corpus of place descriptions harvested from the Web to investigate the way of extracting salient features as landmarks based on human spatial knowledge.

The **NL** parsing is used to extract locative expressions in terms of a set of triples for each place description. A triplet consists of three elements \(<l, s, r>\): an object to be located (locatum \(l\)), a reference object (relatum \(r\)), and their spatial relation (\(s\)). For example, the descriptions can be transformed into multiple sets of triplets by using the **NL** parsing method developed in Khan et al. (2013) and Liu et al. (2014).

With regards to the place graph construction, a set of triplets are homeomorphic to a place graph which is defined in the graph \(G = (V, E)\), where \(V\) is a set of nodes representing unique locata and relata, and \(E\) a set of edges representing the spatial relations between them. Thus, a place graph is, more specifically, a property graph, originally introduced in Hidders (2002).
In such effort towards understanding the mental representation of a place, or in general, better human-machine interaction, this research addresses the dynamic sketch map drawing strategy to generate sketch maps from the extracted spatial information of unrestricted NL place descriptions, which may include ambiguous or uncertain spatial relations. In many situations, such as emergency response, having a machine-generated sketch from place descriptions could support human decision making.

The approach of harvesting large corpora from the Web is developed and applied for generating place graphs. The approach consists of three main phases: an efficient strategy for harvesting relevant web pages that include place descriptions related to a particular environment, extracting triplets from the descriptions, and generating place graphs from these triplets.

This research also develops the similarity matching process which takes into account a composite place graph. The composite graph integrates spatial objects and their relations extracted from individual place descriptions. Corresponding nodes among graphs are identified via similarity measures, using a combination of three types of similarity scores: string, linguistic, and spatial. The matching process can be applied to the corpus of place descriptions harvested from the Web. As a result, the composite graph can be derived from individual place graphs. The graph provides a place model abstracting collective human spatial knowledge, capable of signifying landmark candidates as cognitively significant objects.

Lastly, the landmark extraction model is developed and applied to the composite place graph, using the text classification that categorizes the descriptions according to their context. After the classification, the (potentially large) composite place graph can be generated from the descriptions, reflecting the collective human spatial knowledge in the target environment. The landmark extraction model proposed in this research also targets a mechanism to fully automatically extract landmarks with relative significances from a composite place graph.

1.4 RESEARCH SCOPE

The scope of this thesis consists of four main phases, namely: building place graph and its representation, harvesting large corpora for generating place graphs, similarity matching for integrating spatial information, and landmark extraction from web-harvested place descriptions.

First, this research focuses on the implementation of algorithms based on cognitively motivated heuristics, and evaluating the automated process, in order to automatically produce sketch maps from the spatial content of place descriptions.
Second, this research proposes an approach of harvesting place descriptions related to a particular environment from relevant web pages that include the environment, and extracting triplets from the descriptions. Throughout the analysis of text-based information, human spatial knowledge about places is extracted by NLP in the form of triplets of a locatum, a relatum, and a spatial relationship between them.

Third, this research addresses a new approach of resolving ambiguous or synonymous place names from place descriptions by exploring the given relationships with other spatial features. It matches place names from multiple descriptions by developing a novel-labelled graph matching process that relies solely on the comparison of string, linguistic, and spatial similarities between identified places. Importantly, this approach aims to tackle the challenge of description matching — unifying different descriptions of the same place, or overlapping place descriptions — solely based on the information provided in the individual descriptions themselves, without any use of external information such as gazetteers.

Last, this research focuses on developing a landmark extraction model from the place graphs produced by applying the approaches of three phases above, and test the implementation of the proposed model that is fully scalable in spatial coverage, as well as spatial granularity, paving the way towards automated identification of cognitively salient features as landmarks.

1.5 SIGNIFICANCE OF THE STUDY

This research contributes towards automatic interpretation of NL place descriptions, the integration of spatial information extracted from the descriptions, and the improvement of feature matching methods for dealing with spatial semantics, or in a larger scale, to spatial knowledge extraction from place descriptions. The major outcome of this research is a model and specification of efficient algorithms to extract landmarks from unstructured place descriptions, mainly focusing on spatial knowledge from place descriptions in order to identify cognitive landmarks based on the knowledge.

The major significant contributions of this research are:

- An implementation of the dynamic sketch map drawing strategy from NL place descriptions of places, without the use of additional knowledge sources.
- A new approach for generating place graphs from large corpora, which provides an efficient way of harvesting place descriptions for a target environment from the Web.
- A novel approach for matching place graphs with spatial semantics, which generates a knowledge graph that is fully scalable in
spatial coverage as well as spatial granularity, opening the door for a plethora of future applications, from place-based GISs.

- A landmark extraction model based on human spatial knowledge, which provides a wide range of place categories and accommodates different contexts, and thus, provides landmarks for different conversational contexts. Last but not least it is scalable and can be developed into an automated workflow.

1.6 STRUCTURE OF THE THESIS

In the remainder of this thesis, Chapter 2 reviews previous related work with discussion. It lays out the problems of existing approaches and identifies the gaps in relation to the proposed approaches in this study. The major design and specification of the core algorithms proposed in this research are introduced in detail from Chapter 3 to Chapter 6.

Chapter 3 illustrates place graph construction and its sketch map representation, simply called the dynamic sketch map drawing algorithm. Place graphs and sketch maps are constructed from place descriptions. The proposed methodology applies a hierarchical and dynamic sketch map drawing strategy that is inspired by heuristics people apply in their interpretation of place descriptions, in order to accommodate unspecific, flexible and conflicting common language. This chapter ends with some insights on the case study towards automatic interpretation of NL place descriptions.

Chapter 4 describes a novel approach of harvesting large corpora from the Web for generating place graphs. The approach consists of three main phases: an efficient strategy in harvesting relevant web pages including place descriptions related to a particular environment, extracting triplets from the descriptions, and generating place graphs from these triplets. This chapter also discusses the characteristics of the generated place graphs, and identifies further challenges given the well-known flexibility of natural language.

Chapter 5 introduces a novel-labelled graph matching process that relies solely on the comparison of string, linguistic and spatial similarities between identified places. This process uses unstructured place descriptions as an input, and produces a composite place graph with qualitative spatial relations from the descriptions. The performance of this novel process is discussed at the end of this chapter.

Chapter 6 describes a model that supports a fully-automated procedure towards extracting landmarks from unrestricted NL place descriptions, as they reflect human spatial knowledge. This chapter also presents all the implemented algorithms and tools with general discussion on the implementation.

Reviewing the proposed approaches and their experimental results, Chapter 7 presents a detailed discussion, which relates the findings
back to the hypothesis. Finally, the conclusions and future work are drawn in Chapter 8.
This literature review surveys research into place in GIScience, in particular, for translating place descriptions into landmarks. This chapter commences with a review of place concepts and place-related research in GIScience. The chapter then examines in more detail the fundamental research with regards to harvesting place descriptions and NLP, and place graph matching based on qualitative spatial relations. Lastly, the chapter extends to consider landmark concepts and its extraction from the place. In addition, this chapter also discusses previous related work, and points out the differences or similarities with the approaches proposed in this research.

2.1 PLACE IN GISCIENCE

Place is an increasingly important notion in GIScience and the concept of place has a long history in geography and related disciplines. Indeed, a major question is “What exactly is ‘place’?” Since the word ‘place’ was first conceptualized from geographers such as Tuan (1977, 1979), the notion of a sense of place has been studied in many research such as (e.g. Agarwal, 2005; Relph, 1993, 1996), but still remains a complex task as Gärling et al. (1985) said: “place is a concept that is rich in meaning and difficult to define”.

Due to the importance and complexity of place, the demands for place-related research in GIScience have been increasingly acknowledged with regards to human spatial knowledge (e.g. Golledge, 1990, 1995, 1999; Golledge and Stimson, 1997; Goodchild, 2011; Goodchild et al., 2007; Winter and Freksa, 2012; Winter et al., 2016). However, there is not much success in modeling and utilizing place information (Adams and McKenzie, 2013). This is mainly because of vagueness and ambiguity of places by current formal models in GIS. Place in current GIS is usually defined by textual place names associated with coordinate locations, without further consideration on people’s perception and cognition factors (Curry, 1996, 1998) and agreement on its nature (Davies et al., 2009). Consequently, place remains a relatively new and small research area compared to traditional topics in GIScience, and rarely mentioned (Winter et al., 2009). Many attempts were made to identify the properties of place (e.g. Vasardani and Winter, 2015).

This research refers to the general definition and notion of place in GIScience: ‘Places are the conceptual entities that enable cognitive structuring of the spatial aspects of reality’ (Bennett and Agarwal,
and ‘places are typically determined by entities in the geographic environment or by relations between entities in the environment rather than by externally imposed coordinates and geometric properties’ (Winter and Freksa, 2012). The cognitive notion of place is used in this research, comprising both its linguistic and its spatial extensions introduced in Vasardani et al. (2013b) as shown in Figure 2.

![Diagram showing the concept of place, its linguistic extension, and its spatial extension.](image)

Figure 2: The (cognitive) concept of place, its linguistic extension, and its spatial extension

2.2 PLACE DESCRIPTIONS AND NATURAL LANGUAGE PROCESSING

The concept of place captures how people perceive, memorize, reason and communicate about space (Richter, 2013). The important role of place and its externalization in language or sketches, have been broadly recognized (Couclelis et al., 1987; Lynch, 1960; Mark et al., 1999; Vasardani et al., 2013a). People rarely use quantitative (geometry or metric) expressions, but refer to qualitative spatial relations and place names which are highly ambiguous due to vernaculars and non-gazetteered synonyms (Landau and Jackendoff, 1993; Levinson, 2003). Thus, human place descriptions are linguistic expressions and externalizations of what is in the minds of people (Richter, 2013), but human concepts of places are hard to formalize due to their context-dependency and indeterminacy (Bennett and Agarwal, 2007; Burrough, 1996).

In this research, place descriptions are natural language descriptions using locative expressions to describe an environment such as a campus or a city. The expressions refer to places either by their names (i.e. ‘The University of Melbourne’) or by the names of their category (i.e. ‘the campus’), and they may be complex, linking different references by spatial relationships, either explicitly or implicitly (Richter, 2013). The structure of place descriptions has been studied in linguistics research (Jarvella and Klein, 1982; Schegloff, 1972). Place descriptions also reflect the principle of relevance (Sperber and Wilson, 1986). They are selected to be concise or elaborate to avoid disambiguates or uncertainties (Tomko and Winter, 2009). Many place descriptions reveal hierarchical structures by spatial granularity (Plumert et al., 1995; Shanon, 1979) or salience (Couclelis et al., 1987; Stevens and Coupe, 1978).
These place descriptions can be harvested automatically from the Web (Vasardani et al., 2013b). Web harvesting is a common method to collect spatial (or any other) information (Mário et al., 2006; Purves, 2011), because web harvesting is more efficient in collecting large corpora of spatial information than surveys. Web harvesting has been boosted by application programming interfaces (APIs) of prominent sites such as WikiMapia¹, Wikipedia², or GeoNames³. Crowd-sourcing methods are related to web harvesting (Vasardani et al., 2013b). Recently, GIScience has experienced great interest in ‘place’-related research, with the analysis of text-based information such as web documents (Abdelkader et al., 2015; Adams et al., 2015).

In order to interpret place descriptions, there are some approaches of developing classifications to annotate spatial information in text sources, only considering certain aspects such as qualitative spatial relationship (Cristani and Cohn, 2002), place name annotation (Mani et al., 2010), or linguistic ontology (Bateman, 2010; Bateman et al., 2010). Apart from these approaches, linguistic researchers have been working on parsers that can process unrestricted language input for spatial content. For example, a conceptual framework had been presented for the tagging and parsing of text to extract movement information (Hornsby and Naicong, 2009). Other work has studied the semantics of locative expressions of various languages (Kracht, 2002; Zlatev, 2007). Based on the latter, a method was proposed to assign reference objects, locata and spatial relations’ roles to linguistic terms (Kordjamshidi et al., 2011), and a parser was presented by extracting spatial features and qualitative spatial relations between them from natural language descriptions (Khan et al., 2013; Liu et al., 2014).

Specifically, the NL parser developed in Khan et al. (2013); Liu et al. (2014) is used in this research since it enables to extract a set of spatial triplets, by analyzing the locative expressions found in a place description. These triplets represent the features and the spatial relations between these features mentioned in the description. Thus a triplet consists of three elements <l, s, r>: an object to be located (the locatum l), a reference object (the relatum r), and their spatial relation (s). For example, the triplet <Sports Centre, above, Campus> identifies a ‘Sports Centre’ as the locatum, a ‘Campus’ as the relatum, and a relation ‘above’ between them. The concept of triplets is broadly defined and used (e.g. Coyne et al., 2010; Kordjamshidi et al., 2011; Wiebrock et al., 2000; Zlatev, 2007).

Place descriptions are typically produced according to their particular contexts such as the purpose of the communication. This research focuses on text classification of place descriptions to accommodate different conversational contexts. With regards to the task of text clas-

¹ www.wikimapia.com
² www.wikipedia.com
³ www.geonames.org
supervised machine learning techniques have been mostly used, including decision trees (Lewis and Ringuette, 1994; Quinlan, 1993) and support vector machines (Dumais et al., 1998; Joachims, 1998; Liu et al., 2010). These techniques require initial-labeled training set of classified documents. Once a classifier is modeled, new documents are classified automatically. This research choose WEKA, which is widely adopted for text mining. The text classification method of Loh (2008), using a classifier based on a decision tree implemented in WEKA, is used to categorize the place descriptions, because of both fast performance and effectiveness as shown in the previous works (Lewis and Ringuette, 1994; Loh, 2008; Quinlan, 1993).

2.3 Place Graph with Qualitative Spatial Information

Place graphs are a special type of a property graph (Hidders, 2002), introduced as a spatial property graph (SPG) (Vasardani et al., 2013a). In this research, the concept of a place graph is used for representing and integrating spatial information extracted from place descriptions. The set of locata and the set of relata are the vertices of the place graph, while the spatial relations are the labeled edges, directed from locatum to relatum. In this research, place graphs are stored in a graph database since graph databases are commonly used in modelling general or spatial knowledge (Angles and Gutierrez, 2008; Basiri et al., 2014).

Qualitative spatial relations extracted from NL, despite their variety and flexible use, can be represented using formal models of directional, topological, order, and distance relations (Egenhofer and Franzosa, 1991; Egenhofer and Herring, 1991; Frank, 1992; Freksa, 1992; Hernandez, 1991). In particular, there are some research on how the uncertainty and ambiguity of NL relations expressions are dealt with qualitative spatial reasoning. For instance, spatial reasoning with entirely qualitative cardinal directions and distances was introduced by Frank (1992), while a cognitively motivated reasoning approach about relative orientation was proposed (Freksa, 1992). Such formal approaches, however, are based on interpreting spatial relations using specific terminology, rather than a more human-like variety of linguistic expressions. The presented work allows for the variety and flexible use of relations in NL, based on expandable classes of spatial relations.

In English, spatial relations are commonly expressed using prepositions. Such a set of English spatial prepositions and their semantics were analyzed as a way of describing the relationship between objects before (Landau and Jackendoff, 1993). In a different study, the thirty-five different NL spatial relations that were found in the OS
MasterMap for the hydrology domain alone, were examined and their similarities were measured (Schwering, 2007). Independently, a computational model was developed in an attempt to bridge the gap between natural language terms and formal spatial relations (Shariff et al., 1998). In this research it is assumed that semantically similar spatial relations can be mapped to a canonical finite set of relations.

2.4 Qualitative Spatial Representation

Wiebrock et al. (2000) have introduced a visualization approach for spatial layouts from descriptions. Their approach is based on a graph of objects and spatial relations from indoor environment descriptions. The authors focus on the inference of additional relations, and their main interest is in human-robot communication. In this research, the approach is also based on a graph structure, but focuses on spatial features and their relations to outdoor environments, and their plausible configuration on a plane.

Closer to the present work, Wolter and Wallgrün (2012) introduced a way to produce a sketch map from a qualitative scene description, or even from a mixed qualitative-quantitative scene description, by using SparQ, a toolbox for representing and qualitative spatial reasoning (QSR) about space, based on qualitative spatial relations. SparQ, originally introduced in Wallgrün et al. (2007), is based on constraint reasoning, and provides techniques for checking the consistency of qualitative information. However, scenes that include conflicts and do not satisfy the constraints cannot be generated. In contrast to Wolter and Wallgrün (2012), this research applies a dynamic drawing algorithm, which relies on the order of the information in the descriptions, the hierarchical structures identified in them, and a placement decision-making process that deals with possible conflicts. Thus, it incrementally draws the sketch, and in each step it tests several different candidate placements of objects as long as no topological conflict arises, before marking a description as possibly erroneous. A more detailed comparison of the two implementations can be found in Chapter 3.

Bhatt and Wallgrün (2014) presented a conceptual narrative-based architecture for spatial modeling, querying and visualization. The narratives are constructed from spatio-temporal databases, and the narrative-centered model is introduced, particularly focusing on qualitative abstraction and integration, spatial consistency and practical geospatial abduction. Their model focuses on the observable spatio-temporal aspects (e.g., shrinkage, splits, disappearance) of dynamic geospatial phenomena. In contrast, this research concentrates on visualizing spatial information in terms of spatial objects and relations by

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4 The national topographic database provided by Ordnance Survey, Britain’s national mapping agency
the proposed formal model on the basis of NL descriptions, without involving additional spatial databases about urban environments.

2.5 Place Graph Matching and Merging

In information theory and computer science, string matching techniques (Levenshtein, 1966; Pfeifer et al., 1995; Wu and Manber, 1992) have been proposed to deal with efficient searching. Notably, the Levenshtein distance (Levenshtein, 1966) is one of the most popular methods for string matching by measuring the minimum number of single-character insertions, deletions or substitutions it takes to transform one string to the other. The Damerau-Levenshtein distance is similar except that it considers also the transpositions of adjacent characters (Pfeifer et al., 1995). N-grams and the approximate global regular expression print (Agrep) (Wu and Manber, 1992) are also broadly used in the area of information retrieval. The N-gram method considers words as groups of neighbouring letters, while Agrep is designed for a rapid searching. In addition, ontology matching is broadly used as a solution to the semantic heterogeneity problem faced by computer systems (Euzenat et al., 2013). The majority of name-based ontology matching solutions use one or more string similarity measures to determine two concepts’ similarity (Zarembo et al., 2015). In this approach, only the Levenshtein distance will be deployed as a measure of string similarity of place names (Sehgal et al., 2006).

In the area of NLP, WordNet (Fellbaum, 1998; Miller, 1995) has been used in many approaches that measure semantic similarity in textual descriptions (Fellbaum, 2010). Knowledge-based structural similarity, corpus-based similarity in large corpora and combining similarities have been studied (Banerjee and Pedersen, 2002; Leacock and Chodorow, 1998; Mihalcea et al., 2006; Patwardhan and Pedersen, 2006; Pedersen et al., 2004; Resnik, 1995, 2011). Among them, the measure of linguistic similarity is based on the content of information (Resnik, 1995, 2011). Related to a geospatial semantic perspective, a mapping approach between the vocabulary in OpenStreetMap (OSM) and words in WordNet has been introduced (Ballatore et al., 2013). The authors also introduced the semantic similarity ensemble of combining different similarity measures based on WordNet (Ballatore et al., 2014). These approaches rely on knowledge-based structures or the notion of information content, still without considering the similarity of spatial neighbourhoods in terms of spatial relations.

The Matching-Distance Similarity Measure for determining semantic similarity of spatial objects was proposed, especially in the geospatial domain, and is based on comparing the distinguishing features (parts, functions, and attributes) and their spatial relations (is-a and part-whole relations) (Rodriguez and Egenhofer, 2004). However, these relations are just a few from the many commonly used spatial re-
lations of direction, topology, order, and distance (Egenhofer and Franzosa, 1991; Frank, 1992; Freksa, 1992; Hernandez, 1991). Incidentally, similarity assessment based on a graph-theoretical methodology (Nedas and Egenhofer, 2008) has also been proposed before, for spatial queries with cognitively motivated approaches about spatial scene comparisons. The authors also suggested that implicit relations can be derived using composition tables such as those for topological (Egenhofer, 1994; Egenhofer and Sharma, 1993), directional (Papadias and Egenhofer, 1997), as well as combinations of directional and distance relations (Papadias, 1999). In the research of the extensible markup language (XML) application schema matching, a future work was also introduced using spatial topological relations-based knowledge, which can be used in the matching process (Yi et al., 2005). The similarity assessment between scenes (Nedas and Egenhofer, 2008) relies on spatial similarity among their relations to other objects, only considering first-order neighbours. Based on a survey of existing similarity measures, a framework was introduced to specify the semantics of similarity in geographic information retrieval (GIR) (Janowicz et al., 2011). In this thesis, a novel approach is proposed for matching corresponding objects between texts. The proposed approach combines string and linguistic similarities between objects’ names as well as spatial similarity considering first- and higher-order neighbours, combining and extending prior work.

With regards to graph-based matching methods, iterative methods for computing the similarity of the elements of these graphs, such as nodes and edges, have been suggested in the past. One influential iterative approach, motivated by the demands on web searching, has been that of Kleinberg (Kleinberg, 2000). The approach uses text-based search methods to identify a candidate graph containing relevant websites and their neighbours, and computes hub and authority scores for every node in the candidate graph. The idea is based on the concept that two graph elements (e.g., edges or nodes) are similar, if their neighbourhoods are similar. Several other application-oriented algorithms also utilize the idea of recursively computing node similarity scores based on the scores of neighbouring nodes. These are all based on the similarity flooding algorithms (Melnik et al., 2002). These previous approaches concentrate only on structural aspects of graphs to find the corresponding nodes. In this thesis, however, the proposed approach combines structural with other types of similarity in order to cater to the flexibility of natural language expressions.

Toponym resolution comprises geo-parsing which is considered a special case of NER as a standard part of NLP. For example, an NER system based on unsupervised learning was introduced to recognize named-entities (Nadeau et al., 2006). In particular, gazetteer-based toponym disambiguation methods have been suggested for geotagging place names mentioned in Web pages, involving two types of ambigua-
ities (geo/non-geo and geo/geo) (Amitay et al., 2004), for matching each location feature (Sehgal et al., 2006), for detecting the same location entities (called duplicated records) over gazetteer records (Martins, 2011; Zheng et al., 2010), and for matching Points of Interest from different social networks (McKenzie et al., 2014; Scheffler et al., 2012). Such methods of toponym disambiguation can be used for resolving ambiguity of locations and boundaries of official place names, since the geographic references coming from a gazetteered entry provide additional evidence for similarity.

Overall this matching process proposed in this research contributes to the field of GIR, with related work on geo-parsing, place disambiguation, and vague geographic terminology (Jones and Purves, 2008). GIR focuses on finding relevant Web documents by processing spatial user queries, which adds geographic relevance to traditional information retrieval (Janowicz et al., 2011). In its standard process, GIR uses gazetteers or spatial databases to match recognized place names with a geographic location. For example, one approach of linking a geographic query to vector data, geographic dictionaries and an a-priori developed ontology allowed for three types of matching: topological, geographical, and conceptual matching (Mata, 2007). In this research, the matching process also applies an integrated retrieval approach, but only in measures, not in the data sources used. Since this approach focuses on matching geographic information among descriptions of the same area, no external database such as a gazetteer is used.

2.6 LANDMARK EXTRACTION

In a recent book (Winter and Richter, 2014, p. 14–15), we can find the connection between places and landmarks: “Landmarks are points of reference in mental spatial representations. Their function in mental representations is to locate other objects. This function establishes a connection to place, which is another geographic concept structuring space, and perhaps one that is even more elusive than landmarks (Goodchild, 2011; Presson and Montello, 1988). Place also captures the meaning and affordance of a scene, and hence, is rich in structure and complex to communicate.”

In the same context:

“Whichever perspective is taken, the philosophical or the geographic, place covers a different meaning to landmarks. From the philosophical perspective, every object has a place, but not every object is a landmark. From the geographic perspective, places can also function as landmarks, but are then stripped of their rich internal meaning and instead linked with a location.”

In this research that focuses on landmark extraction from place descriptions, we can be more specific. Winter and Richter (2014) pro-
vide a thorough review of the cognitive and linguistic literature on landmarks, including (Couclelis et al., 1987; Downs and Stea, 2011; Lynch, 1960; Sadalla et al., 1980; Siegel and White, 1975; Sorrows and Hirtle, 1999; Tversky, 1993). Lynch (1960) introduced the notion of landmarks which are commonly identifiable objects as external reference points according to commonalities in the structure of the sketches reconstructed from human memory. Siegel and White (1975) considered landmarks as unique configurations of perceptual events. Sadalla et al. (1980) pointed out that landmarks are spatial reference points which help to identify the location of other points. In the research of Couclelis et al. (1987), the anchor points have been called as landmarks which are defined as cognitively salient objects in the environment, and the points are primarily treated as part of a person’s factual knowledge of space in individual cognitive maps. Landmarks are also cognitively salient spatial objects with significant characteristics for constructing a cognitive map of spaces (Downs and Stea, 2011; Sorrows and Hirtle, 1999; Tversky, 1993). The literature highlights the role of landmarks as reference points and anchor points of cognitive representations of the environment.

Sorrows and Hirtle (1999) proposed three categories of characteristics that apply for landmarks in both physical and electronic spaces: visual, cognitive, and structural landmarks. With the categorization of landmark characteristics, Raubal and Winter (2002) use visual salience, semantic salience, and structural salience in order to measure a total salience value for extracting landmarks. Most existing models based on the categories have also been further studied (Klippel and Winter, 2005; Raubal and Winter, 2002; Winter, 2003; Winter et al., 2005). In addition, several innovative approaches have been introduced as well. For instance, Elias (2003) proposed data mining algorithms to detect landmarks at every potential choice point (i.e., intersection). Caduff and Timpf (2008) proposed a framework that contributes to the overall salience of geographic objects. Their framework bases on the initial assumption that appearance of landmarks is strictly visual. As introduced by (Sadeghian and Kantardzic, 2008), current landmark detection methods operate by constructing a neighborhood around a street intersection, detecting the building relative to the other buildings in the neighborhood by applying building attributes, and labeling the buildings as the local landmark. Duckham et al. (2010) explored categories of features to determine suitability as a landmark. Some state of the art approaches (Quesnot and Roche, 2014; Zhu and Karimi, 2015) have been addressed considering the frequency of check-ins from social networks as a local geographic knowledge.

Winter and Richter also provide a review of approaches to extract landmarks from various sources, from spatial databases to imagery. Most of these approaches are based on three characteristics of objects: visual, cognitive, and structural (Raubal and Winter, 2002; Sorrows
Alternative approaches used data mining in spatial databases (Elias, 2003), evaluations of overall salience of objects (Caduff and Timpf, 2008), or salience of categories of objects (Duckham et al., 2010). Landmarks identification in the relevant papers mostly relies on spatial databases such as network datasets or digital maps. In contrast, this research aims to the development of formal model for extracting landmarks based on human spatial knowledge extracted from place descriptions.

Also relevant, are computational approaches for extracting landmarks in electronic environments. Mukherjea and Foley (1995) developed an algorithm to identify landmarks based on the analysis of the web, using four characteristics: the in-degree and out-degree of a node, its second-order connectivity, and its back second-order connectivity. Later, this has been refined to characterising the importance of a node by its network connectivity, accessed frequency, and depth (Mukherjea and Hara, 1997). Moreover, centrality has been used to characterize the importance of a node in all areas of network analysis (Newman, 2010). The presented landmark extraction model in this thesis is also based on a graph structure. In particular, connectivity and in-degree centrality in the place model are used for identifying landmarks.

Denis et al. (1999) extracted landmarks manually from NL route descriptions, using the frequency of occurrence. Tomko (2004) used the prominence of spatial objects considering their rank from web searches, while Tezuka and Tanaka (2005) aimed at extracting landmarks from texts taken from the web, using statistical measures such as document frequency and spatial sentence frequency. Recently, Murai et al. (2011) considered the most frequently mapped objects as landmarks, detected from textual route descriptions collected from the web. In contrast to those models using only the frequency of objects in descriptions, this research evaluates landmark characteristics as these emerge from collective human spatial knowledge. Again, other approaches use frequencies of check-ins (Quesnot and Roche, 2014). In contrast to these models using only the frequency of objects in descriptions, this research focuses on a cognitively motivated approach considering the characteristics of landmarks, such as the role of landmark. In addition, this research aims to extract context-based landmarks on separation of place descriptions classified by their contents (simply called text classification).
People use verbal descriptions to communicate spatial information, externalising relevant parts of their mental spatial representations. In many situations such as emergency response, the ability of a machine to interpret these verbal descriptions could assist in human-machine interaction. However, it still remains a question whether unrestricted NL descriptions of environments or place descriptions, with their potentially underspecified or even conflicting information can be automatically translated in a plausible sketch map.

As a first step in such an endeavour, this chapter presents an automatic approach that translates spatial objects and their spatial relations extracted from verbal descriptions via NLP into a plausible sketch map. The proposed methodology applies a hierarchical and dynamic sketch map drawing strategy that is inspired by heuristics that people apply in their interpretation of place descriptions, in order to accommodate underspecified, flexible and conflicting common language. The methodology is implemented and tested. This chapter ends with some insights for further research towards automatic interpretation of verbal place descriptions.

3.1 INTRODUCTION

Sketch maps are, in this context, two-dimensional representations of features in an environment, and their spatial relations. Previous research concentrates on comparing NL descriptions and sketches that express the same cognitive representation (e.g. Denis, 1997), assessing the information presented on a human-made sketch map (e.g. Wang and Schwering, 2009), translating basic descriptions into three-dimensional visualizations based on extracted spatial information (e.g. Tappan, 2008), and on a toolbox supporting constraint reasoning with relational-algebraically founded qualitative spatial calculi (e.g. Wolter and Wallgrün, 2012).

The verbal place description as well as a sketch map drawn by a person, provides a window to a human mental representation of a place. However, both means are generalized and simplified, stripped off from details that may be in mind, but have not been expressed or have been expressed in a vague manner. In order to communicate, however, the person receiving and interpreting a verbal place description will accommodate for these non- or underspecified aspects. Spatial cognition research has identified some cognitive heuristics that people apply in this process. The presented method to interpret a
place description borrows in its dynamic sketch drawing procedure from these heuristics. Accordingly it will produce one such graphical representation of many plausible ones that can be derived from a place description. Overall, the presented method can only aim for topologically consistent rather than reality-matching graphical representations, since in most cases metric information such as orientation or distances is lacking. The term ‘plausible’ then is used in the sense of homeomorphic to (any) graphical representation produced by a human, that is consistent or free of conflicts, in its topological relationships. They visualize mental models constructed from perception or imagination, and which themselves are just one possibility of the mental images they underlie (Johnson-Laird and Byrne, 2002)

The hypothesis is that a plausible sketch map can be automatically produced from spatial objects and their spatial relations extracted from NL descriptions. This approach starts from extracted spatial knowledge of places without the use, at least initially, of additional knowledge sources.

The presented methodology for sketch drawing is based on cognitively motivated heuristics, and evaluating the automated process, in order to automatically produce plausible sketch maps from the spatial content of place descriptions. In addition, some insights are addressed for further research towards automatic interpretation of verbal place descriptions. With its rule-based placement of spatial features, the sketch map algorithm does not capture much of any other aspects of a place, such as its sense, or prominence; it is rather solely designed to depict a spatial configuration on the plane.

3.2 Dynamic Sketch Map Drawing Strategy

The overall workflow of this approach is shown in Figure 3. Input is a set of triplets extracted from a place description using the NL parser developed in Khan et al. (2013) and Liu et al. (2014). The approach is broken down into three parts: a) the spatial relations classification, b) the spatial property graph construction, and c) the dynamic sketch map drawing.

Figure 3: Workflow of dynamic sketch map drawing of place descriptions
This classification allows for standardized spatial relation expressions to be used as labels on place graphs. The qualitative spatial relations are classified by linguistic similarity of their expressions. For this purpose, flexible and expandable classification tables are introduced. These tables map semantically similar spatial relationships to a core set of relations. The mapping by tables does not, however, consider identifying the exact semantics of linguistic expressions of spatial relations. Rather, the classification tables can be modified and extended to accommodate different sets of English prepositions (Landau and Jackendoff, 1993).

The classification table (Table 1) covers currently five types of spatial relations: directional, topological, order, distance, and ternary relations. The table setup shows already deliberate choices. For a first example, ‘above’ and ‘below’ are considered here horizontally (and later, in the placement algorithm, interpreted equal to the plane division of ‘north’ and ‘south’, respectively, in the heuristics), since people usually orient themselves north-up when describing a place (Meneghetti et al., 2012). For instance, “Sports centre above Campus” is interpreted as ‘Sports centre’ being horizontally above ‘Campus’ on a North-Up oriented map. Only cases of ‘under’ or ‘underneath’ are interpreted vertically, as in “Carpark underneath University Square”. Second, the implemented topological relations ‘in’, ‘on’, and ‘within’ were mapped to a formally defined ‘inside’. Third, the qualitative order relations ‘next’ and ‘beside’ are both mapped to ‘next’. Fourth, the implemented relative distances between locatum and relatum are generalized here into three distance ranges: ‘near’, ‘middle’ and ‘far’. Comparatives and superlatives are also mapped to the corresponding range; for example, ‘further’ and ‘furthest’ are mapped to ‘far’. If there is no distance information, the default range ‘middle’ is assumed by the placement algorithm. Distance relation expressions can also be used as quantifiers for other relations, such as ‘far north’. In this case, two relations are assumed between relatum and locatum: a distance and a directional one. Last, triplets usually contain binary relations. To accommodate some ternary relations, such as ‘between’ and ‘across’, these are broken down into pairs of binary relations, with the same locatum and two different relata, in their sequence maintaining the order with which these relata were introduced. While some particular cases such as ‘opposite’ may have a tertiary meaning (or a binary extended by an additional intrinsic reference frame) this additional information does not come out of the common language, but refers to a shared knowledge of orientation which cannot be extracted by NLP alone.
The result of the classification is a list of triplets with standardized spatial relations. The processed triplets are input to the place graph construction.

Table 1: Qualitative spatial relations classification

<table>
<thead>
<tr>
<th>Type</th>
<th>Implemented relations</th>
<th>NL relations</th>
</tr>
</thead>
<tbody>
<tr>
<td>directional</td>
<td></td>
<td></td>
</tr>
<tr>
<td>center</td>
<td>center</td>
<td>center</td>
</tr>
<tr>
<td>north</td>
<td>north, northern, N</td>
<td>north, northern, N</td>
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<td>west</td>
<td>west, western, W</td>
<td>west, western, W</td>
</tr>
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<td>north east</td>
<td>north east, NE</td>
<td>north east, NE</td>
</tr>
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<td>north west</td>
<td>north west, NW</td>
<td>north west, NW</td>
</tr>
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<td>south east</td>
<td>south east, SE</td>
<td>south east, SE</td>
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<td>south west</td>
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<td>south west, SW</td>
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<td>right</td>
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<tr>
<td>front</td>
<td>front</td>
<td>front</td>
</tr>
<tr>
<td>back</td>
<td>back, behind</td>
<td>back, behind</td>
</tr>
<tr>
<td>above (horizontally)</td>
<td>above, upper, top of, up</td>
<td>above, upper, top of, up</td>
</tr>
<tr>
<td>below (horizontally)</td>
<td>below, lower than, bottom of</td>
<td>below, lower than, bottom of</td>
</tr>
<tr>
<td>under (vertically)</td>
<td>under, underneath</td>
<td>under, underneath</td>
</tr>
<tr>
<td>opposite</td>
<td>opposite, other direction from, other side of</td>
<td>opposite, other direction from, other side of</td>
</tr>
<tr>
<td>topological</td>
<td>surround</td>
<td>surround</td>
</tr>
<tr>
<td>inside</td>
<td>in, inside, into, within, on</td>
<td>in, inside, into, within, on</td>
</tr>
<tr>
<td>outside</td>
<td>outside</td>
<td>outside</td>
</tr>
<tr>
<td>order</td>
<td>along, down or up the hill</td>
<td>along, down or up the hill</td>
</tr>
<tr>
<td>after</td>
<td>after</td>
<td>after</td>
</tr>
<tr>
<td>before</td>
<td>ahead, before</td>
<td>before</td>
</tr>
<tr>
<td>next</td>
<td>next, beside</td>
<td>next, beside</td>
</tr>
<tr>
<td>distance</td>
<td>close, near, nearby, adjacent, around</td>
<td>close, near, nearby, adjacent, around</td>
</tr>
<tr>
<td>middle</td>
<td>middle, no information</td>
<td>middle, no information</td>
</tr>
<tr>
<td>far</td>
<td>far, further, furthest</td>
<td>far, further, furthest</td>
</tr>
<tr>
<td>ternary relation</td>
<td>between</td>
<td>between</td>
</tr>
<tr>
<td>across</td>
<td>across (in a particular case)</td>
<td>across (in a particular case)</td>
</tr>
</tbody>
</table>

3.2.2 Place graph construction

A set of triplets are homeomorphic to a place graph, and are expected to have unique feature names. Thus, a place graph is, more specifically, a property graph, originally introduced in Hidders (2002): the vertices of the graph represent spatial features, and the edges represent the spatial relations between the features. Furthermore, the place graph is directed due to the asymmetry between locata and relata.
In order to construct the place graph, the input triplets are processed in order of their appearance in the parsed text. From each triplet $i$, the locatum $l$, spatial relation $s$, and relatum $r$ are extracted. Then two vertices, $l$ (outgoing) and $r$ (incoming) are created and linked with a directional edge labeled with $s$, unless the vertices already exist. If $s$ is a ternary relation such as ‘between’, it is decomposed into two binary relations that share the same locatum $l$ in the parsing process, and are represented with two bi-directional edges, showing the existence of one $l$ and two $r$s. These edges are also labeled with a unique identifier in their property value to identify the two bi-directional edges in a graph that describe one ternary relationship.

3.2.3 Dynamic sketch map drawing process

The generation of a sketch map is guided by the place graph structure. The expected outcome is a plausible representation of the relationships among spatial features encoded in the graph. This step allows for a sequential and hierarchical dynamic drawing operation, which considers the following cognitively motivated heuristics.

- **Sequential order.** The sketch map drawing process follows the order of triplets extracted from the description, since people usually interpret a description in the same sequential manner (Brunye et al., 2010). Therefore, if contradicting information about the same pair of locatum and relatum appears further down the triplet list, more weight is placed on the information first processed.

- **North-Up orientation.** The heading of the spatial features without any orientation information is ‘North’ by default, since the information represented in a mental map is preferentially North-Up oriented (Meneghetti et al., 2012).

- **Dynamic drawing process.** The shape of a rectangle representing a feature can be dynamically enlarged, shrunk or moved when new information is added, following the way that people act according to Grice’s maxim when conveying information (Grice, 1975).

- **Hierarchical structures.** In a sketch map, rectangles can contain other rectangles, resembling hierarchical relations in cognitive maps (e.g. Hirtle and Jonides, 1985; McNamara et al., 1989; Richter et al., 2013).

- **Cognitive adequacy and preferences.** This approach is inspired by cognitive adequacy and preferences of topological spatial relations from an empirical investigation (e.g. Knauff et al., 1997; Renz et al., 2000) on various spatial configurations.
• **Reference frame selection.** The reference frame selection relies on the premise that people usually select a single reference frame to define a spatial relation and the selection process is assisted by inhibition of the non-selected frames (Carlson, 1999; Carlson-Radvansky and Irwin, 1993). In this approach, therefore, a ‘double cross’ of absolute cardinal directions is selected as a single reference frame for placing spatial objects in a sketch map.

**Initial process**

To draw spatial features on a blank canvas, a container of the described environment is assumed as a spatial reference frame for placing $l$ and $r$. A general reference frame is introduced in the form of a ‘double cross’ of absolute cardinal directions (Frank, 1996). The ‘double cross’ is applied to both the extrinsic reference frame of the container, and the intrinsic reference frame of each feature for placing other spatial objects around it. In the reference frame, the heading of features without any orientation information is ‘North’ by default, according to related research about mental representations derived from spatial descriptions being often North-Up oriented (Meneghetti et al., 2012).

To generate a plausible sketch map, the algorithm follows the order of triplets extracted from each description. This major design decision results in a certain order of conflict resolution. It borrows from cognitive preferences, since a person has created the source description in this order, and another person would interpret a description in the same sequential order (Brunye et al., 2010).

**Qualitative spatial directions and distances calculus**

The implemented qualitative spatial direction and distance calculi are based on the directions with a neutral zone. Thus the double cross divides the plane for each relatum into nine regions including a central neutral area (Frank, 1992): {center, east, south east, south, south west, west, north west, north, north east}. To represent a qualitative spatial relation $s$ between $l$ and $r$, each locatum is assigned its own directional vector based on the eight directions plus center (a null vector), as well as one of the three distances for scaling the vector: {close, middle, far}. Accordingly, the position of $l$ with regard to $r$ can be expressed by Equation 1.

$$P_l = P_r + \vec{v} \ast d$$  \hspace{1cm} (1)

- $P_l$ = Position of $l$
- $P_r$ = Position of $r$
- $d$ = Distance scalar {close=1, middle=2, far=3}
• $\vec{v}$ = Cardinal normal vector \{\(\vec{v}_0\)-center, \(\vec{v}_1\)-east, \(\vec{v}_2\)-south east, \(\vec{v}_3\)-south, \(\vec{v}_4\)-south west, \(\vec{v}_5\)-west, \(\vec{v}_6\)-north west, \(\vec{v}_7\)-north, \(\vec{v}_8\)-north east\}

Placing \(l\) is derived from the calculus as shown in Figure 4. For example, if \(l\) is ‘close’ to \(r\), and to the ‘north east’ of \(r\), the relative location of \(l\) will be calculated to be in the position (1,1), at least initially. If \(l\)’s placement creates conflicts with other, already placed features, the position of \(l\) can be moved by adding an adjustment vector incrementally until the conflict is resolved. Hence, order matters.

Figure 4: Placing \(l\) from \(r\) according to Equation 1

Figure 5 shows the possible set of candidate regions \(C\) of \(l\) in the double cross of \(r\) for all the classified spatial relations. The set \(C\) of \(r\) is defined by the meaning of the classified spatial relations based on the reference frame with a default North-Up orientation. Therefore, the \(C\) for ‘around’ or ‘opposite’ will be anywhere, and ‘below’ or ‘front’ will be south of the \(r\) in terms of horizontal and allocentric perspective. For the ternary relations, the \(C\) of \(l\) for ‘between’ will be determined by \(r_1\) and \(r_2\). The relation ‘under’ is an exception and is considered as a vertical ‘touch’ relation (instead of a horizontal, two-dimensional one).

**Hierarchical structure based dynamic drawing**

Place descriptions include conceptual boundaries (or regions), as well as complex objects with interior structures. Such descriptions require
Figure 5: Candidate regions of locatum based on the cardinal zones

hierarchical reasoning in the placement process. The root-level object, the canvas, is a container of various first-level features out of the place description. These objects can, in turn, contain finer grained features.

Features are drawn as rectangles. These rectangles can be enlarged, shrunk, or moved to accommodate a new rectangle on the canvas. For example, if there exists a spatial relation ‘inside’ between two features, then the reference rectangle is enlarged to make space for the new feature. On the canvas, the ‘inside’ relation is represented as the topological relation ‘r contains l’. Figure 6 shows an example of a hierarchical sketch structure following a place description. In the special case of vertical spatial relations, e.g., a spatial relation ‘l under r’, two rectangles are allowed to overlap, i.e. showing the topological relation ‘r overlaps l’.

Placement Decision Making

The placement decision-making algorithm is designed to resolve conflicts that may arise with existing features when new information is added to the sketch map, by ensuring the consistency of spatial relations. The algorithm incrementally records the history of decisions of each feature placement and all their potential alternative placements. It is based on a linked list structure with nine cardinal zones for candidate alternative directions. The direction relations are stored in a one-dimensional array for representing the cardinal zones (v0-center, ... , v8-north east) as integers from 0 to 8. For example, when a feature is placed in the center, its current directions array is [1,0,0,0,0,0,0,0,0]. The direction arrays for all features are logged in the history. The specific algorithm of the placement decision making is introduced in Algorithm 1.

When relocation of a feature is necessary to resolve a conflict, the history log is revisited, and alternative candidate positions are calcu-
lated by multiplying the current candidate directions and the previous candidate directions in the recent order of history (line 9). Then an alternative candidate position is selected (line 12). If the new position also creates conflict, the rest of the alternatives are considered in a depth-first manner, until a suitable placement is found (line 19 to 22). If all alternatives have been exhausted without conflict resolution, then a potential error in the description is flagged (line 26), and the feature is not placed, unless further information about it is revealed.

*Overall process*

For every iteration (line 10) in Algorithm 2, \( R_i \) is the \( i_{th} \) unique relatum \( r \). The unique \( r \) plays a key role in recognizing all locata \( l \) related to it for drawing them on the sketch map. Each \( R_i \) (excluding the container if it is defined at all) is placed at the center of the sketch map if no other information about its absolute cardinal direction exists. Otherwise, it is placed in one of the nine zones of the container, according to its default candidate zone. The placement of \( R_i \) may be adjusted to avoid conflict with existing features on the map, using Algorithm 1. After placing \( R_i \), its position is recorded in the history log. Next, the positions of all the \( l \)s associated with \( R_i \) are determined by using Equation 1 according to the classified spatial relations.

For example, Figure 7 shows the dynamic sketch map drawing steps for a set of triplets. \( O_1 \) is placed in the center of the sketch map, anchoring the rest of features around it, while ‘Campus’ is defined as a container. \( O_2 \), which is ‘East’ of \( O_1 \), can be placed in one of the three
Algorithm 1 Algorithm of placement decision making process

1: \textbf{procedure} \textsc{AdjustPlacement}(\textit{currObj}) \Comment*[h]{The \textit{currObj} can be \textit{l} or \textit{r}.}
2: \hspace{1em} \textit{isFound} \leftarrow \text{False}
3: \hspace{1em} \textit{currDirection} \leftarrow \text{GetDirection (\textit{currObj})}
4: \hspace{1em} \Comment*[h]{Check all logged candidate regions from recent history to the oldest one.}
5: \hspace{1em} \Comment*[h]{The \textit{currObj} can be \textit{l} or \textit{r}.}
6: \hspace{1em} \textbf{for} \textit{i} \leftarrow \textit{n} \leftarrow 1, 0 \textbf{do} \Comment*[h]{\textit{n} is the number of the object’s history.}
7: \hspace{2em} \textit{prevObj} \leftarrow \text{currObjHistory[i]}
8: \hspace{2em} \textit{prevDirection} \leftarrow \text{GetDirection (\textit{prevObj})}
9: \hspace{1em} \textit{tempDirection} \leftarrow \text{currDirection * prevDirection} \Comment*[h]{multiplication of 3 by 3 matrices}
10: \hspace{1em} \Comment*[h]{Check all logged candidate regions from recent history to the oldest one.}
11: \hspace{1em} \textbf{for} \textit{j} \leftarrow 0, 8 \textbf{do} \Comment*[h]{For checking all nine directions,}
12: \hspace{2em} \textbf{if} \textit{tempDirection}[\textit{j}] \Comment*[h]{if one of the nine directions is valid,}
13: \hspace{2em} \hspace{1em} \textbf{then} \Comment*[h]{if one of the nine directions is valid,}
14: \hspace{2em} \hspace{2em} \textit{SetDirection (\textit{currObj, tempDirection}[\textit{j}])} \Comment*[h]{set the direction of the \textit{currObj}.}
15: \hspace{2em} \hspace{2em} \textit{isFound} \leftarrow \text{True} \Comment*[h]{set the \textit{isFound} to \text{True}.}
16: \hspace{2em} \hspace{2em} \textbf{break} \Comment*[h]{set the \textit{isFound} to \text{True}.}
17: \hspace{2em} \textbf{end if} \Comment*[h]{the end of the loop \textit{j}}
18: \hspace{2em} \textbf{end for} \Comment*[h]{the end of the loop \textit{i}}
19: \hspace{2em} \textbf{end if} \Comment*[h]{If already adjusted in this history, stop checking the history.}
20: \hspace{1em} \textbf{if} \textit{isFound} \Comment*[h]{Log the error.}
21: \hspace{2em} \hspace{1em} \textbf{then} \Comment*[h]{Log the error.}
22: \hspace{2em} \hspace{2em} \textit{RedrawObj (\textit{currObj})} \Comment*[h]{The \textit{currObj} is replaced by the new direction.}
23: \hspace{2em} \hspace{2em} \textit{break} \Comment*[h]{Log the error.}
24: \hspace{2em} \textbf{end if} \Comment*[h]{the end of the loop \textit{i}}
25: \hspace{1em} \textbf{if} \textit{isFound} = \text{False} \Comment*[h]{Log the error.}
26: \hspace{2em} \textit{WriteError (\textit{currObj})} \Comment*[h]{Log the error.}
27: \hspace{2em} \textbf{end if} \Comment*[h]{Log the error.}
28: \textbf{end procedure} \Comment*[h]{Log the error.}

zones \{north east, east, south east\} according to the possible candidate regions for ‘East’ around \textit{O\textsubscript{1}}, and of distance ‘middle’ by default (since there is no other distance information). Here, \textit{O\textsubscript{2}} is placed in the east zone of \textit{O\textsubscript{1}} because direct relations \{north, east, south, west\} have higher priority than composite directions \{north east, south east, south west, north west\} in this algorithm, and the position of \textit{O\textsubscript{2}} is determined by using Equation 1. \textit{O\textsubscript{3}} and \textit{O\textsubscript{4}} are similarly placed in one of the candidate regions according to their \textit{s}. Finally, the rectangle of \textit{O\textsubscript{4}} is enlarged and \textit{O\textsubscript{5}} is placed within \textit{O\textsubscript{4}}, as their relation is \textit{inside}.

3.3 Experiment

In order to test the above Algorithms 1–2 and support the hypothesis, a case study has been conducted with human participants for collecting campus descriptions as well as generating human-generated sketch maps. The case study consists of a set of \textit{NL} descriptions of the University of Melbourne’s Parkville campus. The descriptions were submitted by a group of graduate students with varying degrees of familiarity with the campus. Students were asked to produce the descriptions from memory, as if explaining to a new student the layout of the university campus. No further directions or expectations for the descriptions were provided. Each description was parsed using the \textit{NL} parser developed in Khan et al. (2013) and Liu et al. (2014). A manual completion of the parsing into triplets was necessary due to
Algorithm 2 Algorithm of dynamic sketch map drawing

1: procedure DrawSketchMap(triplets)  \(\triangleright\) Triplet\((l, s, r)\)
2: \(\triangleright\) Classify \(s\) according to the defined classification tables.
3: \(\triangleright\) ClassifyRelationships (triplets)
4: Placegraph \(\leftarrow\) GeneratePlaceGraph (classifiedTriplets)
5: uniR \(\leftarrow\) FindUniqueR (triplets)
6: \(\triangleright\) A single root-level container like ‘Campus’
7: SetMainContainer ()
8: \(\triangleright\) As a reference frame for cardinal directions
9: \(\triangleright\) Placegraph
10: for \(i \leftarrow 0, n - 1\) do \(\triangleright\) Process all \(R\) in sequence of the triplets.
11: \(R_i \leftarrow\) uniR\([i]\) \(\triangleright\) \(n\) is the number of unique \(R\).
12: \(\triangleright\) If current \(r\) already existed on the sketch map,
13: if IsExistOnMap\((R_i)\) then
14: \(\triangleright\) replace the \(R_i\) by checking the history.
15: \(\triangleright\) Otherwise, place the \(R_i\) as a rectangular feature.
16: \(\triangleright\) Draw\(R_i\)
17: end if
18: WriteHistory \((R_i)\) \(\triangleright\) Write a log of the \(R_i\)’s placement.
19: \(\triangleright\) \(e\) is the number of the \(R_i\)’s edges.
20: \(e \leftarrow\) GetEdgeNum\((PlaceGraph, R_i)\)
21: for \(j \leftarrow 0, e - 1\) do \(\triangleright\) Process the associated \(l\) in sequence of the triplets.
22: \(l \leftarrow\) GetVertexLAt \((PlaceGraph, j)\)
23: \(s \leftarrow\) GetEdgeAt \((PlaceGraph, j)\)
24: \(r \leftarrow\) GetVertexRAt \((PlaceGraph, j)\)
25: \(\triangleright\) If \(l\) already exist on the sketch map,
26: if IsExistOnMap\((l)\) then \(\triangleright\) replace the \(l\) by comparing the history.
27: \(\triangleright\) Otherwise, place the \(l\) as a rectangular feature.
28: \(\triangleright\) Draw\(L(i, l, s, r)\) \(\triangleright\) Draw the \(l\) according to Equation 1.
29: else
30: \(\triangleright\) Write a log of the \(l\)’s placement.
31: end for
32: end for
33: Visualization () \(\triangleright\) Visualize a plausible sketch map after scaling and labeling.
34: end procedure

The limited accuracy of current automatic parsing. In total, 42 campus
descriptions were collected and tested to verify the robustness of the
prototyped algorithms. For instance, Table 2 shows Description #1.

The found triplets were classified according to Table 10. Table 3
shows a set of the classified triplets from Description #1. The order in
this table follows the sequence of appearance in Description #1. Any
spatial relation not yet in the classification tables can be added at this
stage. The results of this step were 42 ordered sets of triplets with
standardized relations and resolved synonym ambiguities.

In the second step, 42 place graphs were constructed. Figure 8
shows the place graph constructed from Description #1. Then, in the
final step, plausible sketch maps from the graph are produced by
Algorithms 1 and 2, using Equation 1. For all 42 place descriptions,
‘Campus’ was considered as the container because of the specific task
asked from the participants. Some place descriptions did not contain
a reference to ‘Campus’.

The testing of the methodology and its implementation is based on
the assessment whether a sketch map is plausible, i.e., topologically
free of conflicts given all the facts from the triplets. In order to test this
The campus covers a substantial area. In the center are the original “old” buildings that were built when the university first opened many decades ago. These buildings housed the faculty of physics and arts, among others. These buildings can be easily identified by their older style of architecture and brick composition, the concrete archways down each corridor, and the iconic clock tower that can be seen from most parts of the campus. Directly to its south is an open square that acts as an intersection for students to travel from one part of the university to the other. There is a carpark directly under the square. To the West is the Baillieu Library. To the east is the general hall that is used as an examination venue and as a host to other major events like graduation. The Union House is located to the North of the old buildings. The Union House has a cafeteria and also is the hub for most student association activities (SAA). The Engineering departments are located on the South East corner of the campus. If you walk further south of the engineering department, you will reach Grattan Street. Pass the street and walk further down past the public park and you will reach the Law faculty. Most of the sports-related venues like tennis courts, swimming pools and racetracks are located on the opposite side, that is, to the furthest north of the campus. If you can find your way around these spots you can eventually orientate yourself to the other buildings you may need to find in the future. If that fails, you can always ask around or use the conveniently placed maps set up around the entire campus. Finally, if you would like to know more about the hidden gems of quirky spots around campus, the best places for coffee and interesting historical sites, then you are asking the wrong person. Good luck!
Table 3: Classified triplets of NL parsing output from Description #1

1. <Old buildings, center, Campus>
2. <Faculty of Physics, inside, Old buildings>
3. <Faculty of Arts, inside, Old Buildings>
4. <Clock Tower, inside, Old buildings>
5. <Open square, far south, Clock Tower>
6. <Carpark, under, Open square>
7. <Baillieu Library, west, Clock Tower>
8. <General Hall, far east, Clock Tower>
9. <Union House, north, Old buildings>
10. <Cafeteria, inside, Union House>
11. <SAA, inside, Union House>
12. <Engineering Departments, south east, Campus>
13. <Grattan Street, south, Engineering Departments>
14. <Public park, south, Grattan Street>
15. <Law Faculty, south, Public park>
16. <Tennis courts, opposite, Campus>
17. <Swimming pools, opposite, Campus>
18. <Racetracks, opposite, Campus>
19. <Swimming pools, far north, Campus>
20. <Racetracks, far north, Campus>
21. <Tennis courts, far north, Campus>

Figure 8: Spatial property graph on the example of Description #1

ated ones. In order to perform a fair test, participants were not aware of the algorithms. In total 20 manually produced sketch maps were generated since each subject produced five sketch maps from a set of five randomly chosen descriptions by four subjects. Thus, the assessment was conducted in two ways, one by checking the topological consistency of the 42 automatically generated sketch maps given all the facts from the triplets, and the other by measuring a similarity score between two sketch maps themselves about 20 manually produced maps.
Firstly, in order to check the topological consistency of the 42 automatically generated sketch maps, given all the facts from the triplets, the corresponding relations were specified according to the extracted relations after NL parsing, and the consistency was checked under the researcher’s judgment since many plausible representations can be derived from a description. As a result, all compared sketch maps were topologically homeomorphic, with the exception of some cases involving features touching street segments in human sketches (the algorithm always draws features disjoint if no other information is given), or underground features, where people sketched ‘under’ as a horizontal ‘inside’, while in the automated sketch map procedure ‘under’ is drawn by ‘overlap’. For instance, Figure 9 shows a human produced sketch map and an automated sketch map for Description #1. The automatically generated sketch map is topologically homeomorphic to the manually produced one, except feature ‘Public Park’ touching feature ‘Grattan Street’ and feature ‘Carpark’ being under ‘Open Square’. Since the differences can be attributed to different rules for drawing features, which do not significantly affect the overall topology of the layout, there is strong support for the hypothesis of this work. More importantly perhaps, the algorithm shows a complete sketch map, while in this example the manually produced sketch map is missing two features (‘Cafeteria’ and ‘SAA’).

Secondly, sketch similarities between the automatically generated sketch maps and the human generated ones were measured considering object similarity and relational similarity components as introduced by Nedas and Egenhofer (2008). The object similarity is calculated by dividing the number of matched object pairs between two sketch maps by the number of identified unique objects on two sketch maps. The relational similarity is measured based on the consistency
of corresponding binary relations among the matched object pairs of two sketch maps in terms of cardinal directions and topological relations, respectively. The binary relations of each sketch map were specified from each qualitative sketch description composed of base relations in a cardinal direction calculus (Cardir) and a region connection calculus (RCC8) respectively by using the qualify module of SparQ. The center positions of objects on the metric of each sketch map were used as an input in the Cardir calculus, while the four corners of objects in the RCC8 calculus. The overall sketch similarity score between two sketch maps were calculated by averaging their object similarity and relational similarity scores. Table 4 shows a result of sketch similarity scores (ranging from 0.0 to 1.0) measured from 20 sketch map pairs. This result shows that the automatically produced sketch maps have high similarity with around 0.91 on average, compared with the manually produced sketch maps in terms of object and relational similarity. The highest overall similarity score is 0.98, while the lowest score is 0.83.

Table 4: Sketch map similarity scores of the 20 sketch map pairs between the automatically generated sketch maps and the human generated ones

<table>
<thead>
<tr>
<th></th>
<th>Object similarity</th>
<th>Cardir-based similarity</th>
<th>RCC8-based similarity</th>
<th>Relational similarity</th>
<th>Overall similarity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.96</td>
<td>0.75</td>
<td>0.98</td>
<td>0.87</td>
<td>0.91</td>
</tr>
<tr>
<td>Minimum</td>
<td>0.78</td>
<td>0.64</td>
<td>0.91</td>
<td>0.81</td>
<td>0.83</td>
</tr>
<tr>
<td>Maximum</td>
<td>1.00</td>
<td>0.91</td>
<td>1.00</td>
<td>0.96</td>
<td>0.98</td>
</tr>
</tbody>
</table>

3.4 Chapter Discussion and Summary

The implemented method presented in Chapter 3 is the first step toward automatically producing plausible sketch maps from unrestricted NL place descriptions. This method starts from spatial information extracted from place descriptions by the NL parser that extracts a set of spatial triplets through analyzing the locative expressions found in a place description. A place graph is constructed from the spatial features and relations in the triplets. As evident from the case study of the 42 campus descriptions, the place graphs represented a feasible and reliable structure to store and manage abundant place names and their spatial relations.

To generate a sketch map from a place graph, this research proposed dynamic sketch map drawing algorithms. The case study of drawing sketch maps from the campus descriptions shows that the algorithms are robust enough to produce topologically consistent sketch maps from a variety of complex spatial descriptions. In addition, it is shown that the algorithms are flexible enough to deal with under-
specified NL expressions, with a robust mechanism for topological conflict resolution.

For comparison reasons between the proposed approach and the visualization of SparQ (Wolter and Wallgrün, 2012), a set of triplets with a variety of spatial relations was tested with both tools (see Figure 10).

Figure 11 shows the first result, based on the Triplets 1-5 only. As seen in the outcome, both sketch maps are accommodating the given spatial relations. The processing required to get there, however, is fundamentally different in the two approaches. The dynamic sketch map drawing algorithm directly generates a sketch map in a sequential processing of facts, and with backtracking for conflict resolution. Using the block algebra of SparQ, however, one needs to rewrite different types of spatial relations for applying Allen’s interval algebra (Allen and Waltz, 1983) to relate the X and Y intervals of boxes, since the automatic combination of different types of relations is not yet implemented in SparQ.

In a second experiment, Figure 12 shows the results for Triplets 1-7. These triplets now include a conflict between Triplet 3 and Triplet 7, and a combination of different types of relations between the same spatial features O5 and O6 in Triplets 5 and 6. Since conflicting information cannot be realized in SparQ, a sketch map is not produced in SparQ (only conflict flagged). In contrast, object O4 is placed according to the first-processed information (Triplet 3) in the dynamic sketch map methodology, in order to create a plausible sketch map. Similarly, the combination of complex relations expressed in NL descriptions, such as a combination of distance and directional relations (see Triplet 3), or order and directional relation (see Triplets 5 and 6), are well-handled in the dynamic sketch map methodology.

<table>
<thead>
<tr>
<th>Triplet</th>
<th>Spatial Relation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 &lt;O2, inside, O1 &gt;</td>
<td>Topological relation</td>
</tr>
<tr>
<td>2 &lt;O3, inside, O1 &gt;</td>
<td>Topological relation</td>
</tr>
<tr>
<td>3 &lt;O4, far east, O1 &gt;</td>
<td>Distance and directional relation (a combined relation)</td>
</tr>
<tr>
<td>4 &lt;O5, above, O4 &gt;</td>
<td>Directional relation</td>
</tr>
<tr>
<td>5 &lt;O6, next, O5 &gt;</td>
<td>Order relation</td>
</tr>
<tr>
<td>6 &lt;O6, west, O5 &gt;</td>
<td>Directional relation (6 is combined with 5)</td>
</tr>
<tr>
<td>7 &lt;O4, west, O1 &gt;</td>
<td>Directional relation (7 conflicts with 3)</td>
</tr>
</tbody>
</table>

Figure 10: Set of triplets for comparison.

Figure 11: Triplets 1-5: Dynamic sketch map (left) and visualization by SparQ (right).
The same experiment also reveals other differences between a cognitively motivated approach and a logical approach of constraint satisfaction. For example, considering only Triplet 1 and Triplet 2, there is a strong human preference for placing the contained features next to each other (Figure 13a). The dynamic sketch map drawing strategy has these human preferences built-in. Other representations of these two facts (e.g., Figure 13b and c), are correct from a logical perspective, but not preferred. The visualization of SparQ in Figure 11 follows visualization (b).

To illustrate potential uses of the presented methodology, consider an application domain such as emergency call services\(^1\). Table 5 shows a description for an emergency call scenario. While the ‘Cussonia Courtyard’ cannot be located on the official map (Figure 14), the proposed approach generates a plausible sketch map from the emergency call description, which includes the placement of ‘Cussonia Courtyard’. The produced sketch map could be overlaid onto the map, assisting the call operators dispatching help to the appropriate place.

The experiments in this chapter showed that the approach is feasible and robust, by applying the algorithms to 42 campus descriptions. However, the methodology is so far completely agnostic to the semantics of the spatial features, despite potential value for the sketch drawing. For example, in a case study people refer to buildings, street names and other objects. ‘Grattan Street’ is an explicit reference to object type ‘street’. It is an elongated (axial) object, and objects of the type ‘building’ may be connected to the street, and then have their front sides (allocentric orientation) towards the street. Also, we

\(^{1}\) For more information, please find the web sites: “Talking about Place” Project – http://telluswhere.net/, and https://youtu.be/8BnAN_53dcQ
Table 5: Emergency call scenario

- This is the triple zero service, what is your emergency?
- Hello . . . ! I am calling from the University of Melbourne. There has been an accident and a student is in dire straits. We need an ambulance. We are in the Cussonia Courtyard, in the middle of the campus. The Courtyard is next to the clock-tower.
- Which street is the nearest to your location?
- I cannot say from the top of my head, but I think Monash Road is closest to the courtyard. Coming from Monash Road, you can rush through the Old Quad. The courtyard is just behind the Old Quad.

Figure 14: An overlay of the sketch map generated from the emergency call on the map

38

know that a shop or café can be part of a building, but not vice versa. Adding such world knowledge to the sketch drawing algorithm can refine some default placement and drawing choices.

The choice of the ‘double cross’ as a global reference system is motivated by the need to delineate and structure the plane in a uniform way. Cardinal relations provide an initial guide when trying to place features in an empty space, and are thus used first in the sketch map producing algorithm, whenever available.
Place descriptions are individual NL descriptions of places, which are used as a common way to convey spatial information between people, based on their perception or memory of spatial features in an environment and their relations. The descriptions provide a rich source of human spatial knowledge that is complementary to the knowledge found in current space-based GIS.

For the spatial knowledge acquisition, this chapter presents a novel approach of harvesting relevant web pages that include place descriptions related to a particular environment, and generating place graphs from these descriptions.

4.1 INTRODUCTION

Instead of tedious crowd-sourcing of place descriptions (Richter and Winter, 2011), this research investigates whether they also can be harvested from Web platforms such as Wikipedia, business websites, blogs, and social networks services. Throughout the analysis of text-based information, human spatial knowledge about places can be extracted by NLP in the form of triplets of a locatum, a relatum, and a spatial relationship between them. These triplets can be transformed and stored in a graph structure which is useful for managing place graphs, where nodes represent locata or relata, and edges their relations. These place graphs would provide massive support towards place-based GIS, i.e., for diverse applications such as helping navigation systems, supporting human wayfinding process, and automatic landmark identification.

Therefore, this chapter focuses on developing a novel approach of harvesting place descriptions from the Web. The approach consists of three main phases: an efficient strategy for harvesting relevant web pages that include place descriptions related to a particular environment, extracting triplets from the descriptions, and generating place graphs from these triplets. The chapter also discusses the characteristics of the generated place graphs, and identifies further challenges given the well-known flexibility of natural language.
A target environment represents a specific region defined by a boundary, such as the boundary of a city. Relevant web pages are harvested by using place search APIs and Web crawling tools. In general, these services provide the spatial search functions as well as detailed information of found places, especially further uniform resource locators (URLs).

In this experiment, this approach chose the Wikimapia place APIs for selecting start URLs. The main reason is that Wikimapia, as a user-generated place database, would contain place descriptions shared by many people. Another reason is that it provides directly links to Wikipedia documents linked to the searched places, which again are plain language and include abundant place descriptions shared by many users. After selecting start URLs, the web harvesting starts crawling web sites linked to the start URLs and scrapying their contents. The following data sources were discovered as the harvested websites:

- **WikiMapia sites**: User-generated place information including place descriptions
- **Wikipedia sites**: User-generated contents including place descriptions
- **Business sites or official sites**: Place descriptions related to locations of companies, shops, restaurants, and so on
- **Tourist sites**: Popular places and attractions in travel guides
- **Blogs**: Place descriptions focused on individual interests

After hyper text markup language (HTML) parsing to extract texts from the collected sites, the above mentioned NL parser, trained on these forms of texts, is applied in order to extract the spatial information in form of triplets (locatum, relation, and relatum). Each site produces one set of triplets.

Due to the flexibility of natural language and the limitations of current NLP, the extracted triplets include also non-locative expressions. Therefore, the triplets have further been filtered by a set of rules based on the more frequent exceptions found in this experiment, such as:

- Temporal expressions such as ‘in 1999’, and ‘in May’ in a relatum.
- Event or game names such as ‘Melbourne Cup’ in a locatum or relatum
• Composite locative expressions such as ‘Grattan Street and Swanston Street’

• Personal pronouns such as ‘I’, ‘You’, and ‘They’ in a locatum or relatum

In the last step, the individual place graphs generated from the triplets are merged into a composite place graph. Corresponding nodes among graphs are identified via similarity measures, using a combination of three types of similarity scores: typographic, linguistic, and spatial similarities. The typographic similarity, based on existing string matching algorithms, is used to measure the similarity of node names. The linguistic similarity is calculated by a WordNet-based similarity of node names in terms of the words’ meanings. The spatial similarity between nodes represents the level of spatiorelational similarity of the associated neighbours having similar spatial relations. An overall similarity score with equal weights of these similarities controls the matching of corresponding nodes in the graph amalgamation process (the highest precision 0.82), which is introduced more in Chapter 5. The (potentially large) composite place graph reflects the collective human spatial knowledge in the target environment, maintaining also place name synonyms as they were identified.

4.3 EXPERIMENT

An experiment was conducted to show the effectiveness of this approach for harvesting large corpora as well as to discuss the characteristics of the generated place graphs. Figure 15 shows the workflow of the implemented approach to generate place graphs from large corpora. The Wikimapia place search APIs are used for Web crawling and scraping, and the Scrapy tool\(^1\) for its flexibility as a web crawling tool, including the extraction of text from HTML/XML sources. Two target environments were chosen for comparison: Melbourne, Victoria, Australia, and Santa Fe, New Mexico, USA.

![Figure 15: Workflow of generating place graphs](http://scrapy.org)
For Melbourne, first the start URLs of places were searched by using the WikiMapia place search APIs. Figure 16a shows the locations of these start URLs on a map. From the start URLs, the number of web pages extracted by Web crawling is 19,125, and the number of texts extracted by Web scraping is 16,527. From these texts, 2,911 sets of triplets have been identified by NLP, i.e., 17.6% (=2,911/16,527) of the texts contained a recognized place description. Figure 16b shows the composite place graph for Melbourne generated from the descriptions harvested from the Web. This graph contains 2,736 unique nodes, representing the unique place names identified, and 3,221 edges, representing the identified spatial relations between them.

In the same way place descriptions for Santa Fe were extracted. 590 texts were found, and 114 sets of triplets were extracted from these texts. Figure 16c shows the start URLs and 16d the composite place graph for Santa Fe. Despite of the small area of Santa Fe (96.9 km², compared to Melbourne with its 9,990 km²), a total of 238 unique place names and 218 spatial relations between them were identified.

![Figure 16: Place graphs for Melbourne and Santa Fe](image)

In the composite graph of two target areas as shown in Figure 17, 69 unique spatial relations were found. Directional relations have a large portion (55%) in comparison to topological relations (35%) and the other qualitative spatial relations such as order.

The effectiveness of the Web harvesting process was evaluated by computing the number of the texts in which places correctly belong to their target area, and accuracy in percent. For non-georeferenced text geoparsing, an open source library, CLAVIN, has been applied to identify locations from the texts. The locations were checked whether they relate to their target areas, Melbourne and Santa Fe. Note that it only considers automatically extracted geospatial entities from CLAVIN.
(75% accuracy for entity resolution). As a result, the total ratio of relevant texts is 78.5% since 2,373 texts correctly related to their target area from 3,025 texts (2,911 texts for Melbourne and 114 for Santa Fe).

4.4 CHAPTER DISCUSSION AND SUMMARY

This chapter introduced a new approach for generating place graphs from large corpora, which provides an efficient way of harvesting place descriptions for a target environment from the Web, and a strategy of generating place graphs from spatial information extracted from the descriptions via NLP.

The system implemented based on the proposed approach was tested for two different target environments. As a result of the experiment, the main achievement is that the approach harvested place descriptions effectively and generated place graphs based on human spatial knowledge from them. The place graphs also represented a feasible and reliable structure to store and manage abundant place names and their spatial relations.
As presented in Chapter 4, corpora of place descriptions provide a plethora of human spatial knowledge beyond GIS. However, the corpora show in majority non-gazetteered places. Thus, traditional toponym resolution — NER using gazetteers — can fail in many instances. Furthermore, these places are linked with qualitative spatial relations, with all the vagueness and indeterminacy inherent in natural language, which makes a purely geometric analysis of configurations difficult.

For integrating spatial information extracted from the corpora, therefore, this chapter focuses on resolving ambiguous or synonymous place names from place descriptions by exploring the given relationships with other spatial features, as well as developing a novel approach of matching of place names between multiple descriptions.

5.1 introduction

Place information in NL is typically not georeferenced\(^1\) and if taken out of its conversational context, highly ambiguous with regard to its localization. This information can also represent different perspectives on the same locality as these emerge from different individual experience and knowledge. Globally, place names are highly ambiguous, and in addition, place descriptions include vernaculars, non-gazetteered synonyms (written ones may also include abbreviations), or refer to places that are not gazetteered at all.

Thus, the matching of place names between multiple descriptions needs to build on the conversational context of the individual descriptions. The approach suggested in this chapter does this by considering each place name in the context of its spatial relations with other places. Importantly, this approach aims to tackle the challenge of description matching — unifying different descriptions of the same place, or overlapping place descriptions — solely based on the information provided in the individual descriptions themselves, without any use of external information such as gazetteers. To this end, spatial information extracted from each place description is first organized in labeled graph structures. Then a purpose-built graph-matching algorithm identifies corresponding features in different graphs based on a novel approach that uses three types of spatial feature similarity.

\(^1\) There are exceptions, for example, georeferenced Wikipedia entries.
In general, spatial feature similarity can be measured by comparing geometric attributes such as location, size and shape (Winter, 2000). However, such a geometric approach cannot be applied to natural language descriptions with their nominal, relational and qualitative information content and general lack of geometric attributes. In contrast, central to the semantic interpretation of place descriptions are the qualitative relations between spatial features (Papadias and Kavouras, 1994). Hence, this matching process provides an integrated measure of similarity, in which similarity measures considering the spatial configuration are combined with linguistic aspects of the feature names.

5.2 PLACE GRAPH MATCHING PROCESS

Figure 18 illustrates where the suggested approach of matching information from place descriptions sits. The approach consists of mainly three steps: a) NL parsing, b) graph construction, and c) graph matching. With (a-b) described before in Chapters 3 to 4, the main focus of this chapter is, therefore, a matching process for merging multiple place graphs.

![Figure 18: Workflow of the approach to match place graphs from place descriptions](image)

Graph matching aims to find the corresponding spatial objects between place graphs. Figure 19 shows the overall workflow of the matching process, which considers three factors: string, linguistic, and spatial similarity. Similarity based on string matching techniques is an efficient method for determining the degree of typographic similarity between spatial object names, but does not provide the degree of semantic similarity between spatial terms. In contrast, a linguistic similarity measure based on word-to-word matching is an efficient method for determining the degree of semantic similarity between object names, but not for the string similarity. In addition, a spatial similarity measure of a node (object) determines the degree of spatio-relational similarity with neighbouring nodes — nodes connected with an edge to the examined object — connected to the node that neither string nor linguistic similarity provides. Thus, this process provides an exhaustive method for measuring the similarity of...
spatial objects between graphs, given all the information from place descriptions. As a side product, the matching also extracts various synonyms of matched objects.

The overall similarity score plays a key role in finding the corresponding objects. Complexities of the method include determining the weight of each similarity type in the computation of the overall similarity score, and calculating the threshold used to filter the incorrect matching pairs. The three types of similarity scores used to identify the corresponding nodes — string, linguistic, and spatial — are introduced in detail in the following subsections. In addition, the overall similarity scoring method is explained.

![Graph Matching](image)

Figure 19: Workflow of the place graph matching process

### 5.2.1 String similarity

String similarity based on the Levenshtein distance ([Levenshtein, 1966](#)) is computed between each object name in one place graph and each object name in the other place graph. However, object names in NL are not always in their regular forms. Ways to deal with common abbreviations in similarity assessments are in general by mapping tables (here, see Table 6), by rule-based mechanisms, or by machine learning. Rule-based mechanisms profit from some regularities in forming abbreviations, which can be categorized into **shortenings**, **contractions** and **initialisms**. Shortenings of object names use the first few letters of the full name with or without a final period such as ‘St. (St) = Street’. Contractions are abbreviated geographic names or types in which letters from the middle of the full name are omitted, for instance, ‘Rd. (or Rd) = Road’ (type). Initialisms consist of the initial letters of a set of words; for example, ‘Sidney Myer Asia Building’ is reduced to ‘SMAB’.

A similarity between two strings, after replacing abbreviations, is computed by first splitting each string in separate words (if applicable), then comparing all possible word pairs between the strings for their Levenshtein distance, and finally taking the average of the best matches. Thus, a maximum weighted bipartite graph match is
Table 6: Abbreviation examples of spatial object names

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Full name</th>
<th>Abbreviation</th>
<th>Full name</th>
</tr>
</thead>
<tbody>
<tr>
<td>Admin.</td>
<td>Administration</td>
<td>IT</td>
<td>Information Technology</td>
</tr>
<tr>
<td>Archit.</td>
<td>Architecture</td>
<td>Math.</td>
<td>Mathematics</td>
</tr>
<tr>
<td>Bld, Bld.</td>
<td>Building</td>
<td>Rd, Rd.</td>
<td>Road</td>
</tr>
<tr>
<td>Dept, Dept.</td>
<td>Department</td>
<td>Sch.</td>
<td>School</td>
</tr>
<tr>
<td>Eng, Eng.</td>
<td>Engineering</td>
<td>St, St.</td>
<td>Street</td>
</tr>
<tr>
<td>Ent, Ent.</td>
<td>Entrance</td>
<td>Uni, Univ.</td>
<td>University</td>
</tr>
<tr>
<td>Hos, Hos.</td>
<td>Hospital</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: These are common abbreviations in the campus descriptions.

applied, using the Hungarian algorithm (Kuhn, 1955), between two multi-word names (string$_1$ and string$_2$):

$$S_T(string_1, string_2) = \frac{\text{SumOfMaximumWeightedMatch}(string_1, string_2)}{\text{NumberOfMatchingPairs}(string_1, string_2)}$$

As an example, the result of string matching between ‘Swanston St.’ and ‘Grattan Street’ is shown in Table 7. ‘Swanston’ is best matched with ‘Grattan’ (0.375), while ‘St.’ (after expansion) is matched best to ‘Street’ (1.0). The aggregate similarity score between them is 0.69. Thus the strings ‘Grattan Street’ and ‘Swanston St.’ have relatively low similarity because of their different name strings, despite the high similarity in the geographic type.

Table 7: An example of string similarity measure

<table>
<thead>
<tr>
<th>String similarity</th>
<th>Swanston</th>
<th>St.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grattan</td>
<td>0.375</td>
<td>0.286</td>
</tr>
<tr>
<td>Street</td>
<td>0.250</td>
<td>1.0</td>
</tr>
</tbody>
</table>

Aggregate measure of string similarity score: $0.69 = (0.375 + 1.0) / 2.0$

5.2.2 Linguistic similarity

Previous measures of linguistic similarity between words were based on WordNet (Fellbaum, 1998; Miller, 1995) which provides diverse semantic relatedness measures in NLP (Fellbaum, 2010). In this work, the linguistic similarity is based on measuring a normalized value [0 . . . 1] of semantic relatedness using WordNet-based gloss vectors (Patwardhan and Pedersen, 2006). This is because the semantic relatedness correlates strongly with word overlap based on co-occurrence patterns between names or concepts. However, such measures tend to be sensitive, and provide biased and skewed similarity scores (Baltatore et al., 2014). To overcome such limitations, the overall spatial
feature similarity is calculated by combining string, linguistic, and spatial similarities.

Based on the normalized value of word similarity, an object’s name is split into individual words. Subsequently, the linguistic similarity is measured from the results matrix of similarity scores between pairs of words. The linguistic similarity measure is conducted between words (word by word) of object names from different graphs. Thus, measuring the similarity of multi-word names uses a maximum bipartite graph matching, which is averaged by the number of matching pairs between two multi-word names \((\text{word}_1, \text{word}_2)\) defined as:

\[
S_{L}(\text{word}_1, \text{word}_2) = \frac{\text{SumOfMaximumWeightedMatching(} \text{word}_1, \text{word}_2)}{\text{NumberOfMatchingPairs(} \text{word}_1, \text{word}_2)}
\]  

(3)

As an example, the result of linguistic matching between ‘Engineering Building’ and ‘Engineering Department’ is shown in Table 8. The aggregate similarity score between them is 0.75 since ‘Engineering’ is (semantically) exactly matched to ‘Engineering’ (1.0) and ‘Building’ is matched to ‘Department’ with 0.5 because of semantic nearness. The other two word combinations deliver lower total linguistic similarity.

<table>
<thead>
<tr>
<th>Linguistic similarity</th>
<th>Engineering</th>
<th>Building</th>
</tr>
</thead>
<tbody>
<tr>
<td>Engineering</td>
<td>1.0</td>
<td>0.286</td>
</tr>
<tr>
<td>Department</td>
<td>0.250</td>
<td>0.5</td>
</tr>
</tbody>
</table>

Aggregate measure of linguistic similarity score: 0.75 = (1.0 + 0.5) / 2.0

In cases when words cannot be identified in WordNet because they are street name labels for example, or even misspelled, they are processed partially by using only the string similarity measure. For instance, both ‘Grattan Street’ and ‘Swanston Street’ are identifiable as the type of ‘Street’ in linguistic terms, but the names ‘Grattan’ and ‘Swanston’ are not identifiable. They can only be compared using string similarity measures. Moreover, when the numbers of two sets of words are not the same, optimizing the comparison between them becomes an assignment problem, for which a weighted bipartite graph is constructed. The optimal assignment problem is solved by assigning to the edges of the graph the sum with maximal value \((West, 2001)\). As an example, the result of linguistic matching based on the optimized assignment between two sets of words (‘Engineering Building’ and ‘Main South Entrance’) is shown in Table 9. Figure 20 shows a weighted bipartite graph constructed by the words for the optimized assignment. According to the maximum weighted matching, ‘Engineering’ is matched to ‘South’, and ‘Building’ to ‘Entrance’. Thus, the aggregate similarity score is 0.14.
Table 9: An example of linguistic similarity based on the optimized assignment between two sets of words ('Engineering Building' and 'Main South Entrance')

<table>
<thead>
<tr>
<th>Linguistic similarity</th>
<th>Engineering</th>
<th>Building</th>
</tr>
</thead>
<tbody>
<tr>
<td>Main</td>
<td>0.028</td>
<td>0.075</td>
</tr>
<tr>
<td>South</td>
<td>0.031</td>
<td>0.055</td>
</tr>
<tr>
<td>Entrance</td>
<td>0.028</td>
<td>0.245</td>
</tr>
</tbody>
</table>

Aggregate measure of linguistic similarity score: $0.14 = (0.031 + 0.245) / 2.0$

Figure 20: An example of weighted bipartite graph

5.2.3 Spatial similarity

Spatial similarity of objects between two place graphs can be measured by considering the similarities of the associated neighbours having similar spatial relations. For example, if neighbours connected to an object in one place graph are similar to neighbours connected to an object in the other place graph — in terms of the names of the neighbours and the connecting spatial relations — the objects can also be considered similar. The similarity flooding algorithm (Melnik et al., 2002) has been originally designed to measure similarity for structural graph matching between non-spatial models. The flooding algorithm, based on a pairwise connected graph (PCG), matches diverse data structures such as two data schemas or catalogs, by mapping corresponding nodes of two graphs so that the mapping results enable users to choose final matching nodes according to their goals.

The similarity flooding algorithm assumes that objects that have edges connecting them with (structurally) similar neighbours in both graphs, are similar themselves. This concept can be transformed into place graphs, which are property graphs. They consist of spatial features and their labelled spatial relations, and the semantics of spatial relations must be considered.

Therefore, building upon similarity flooding, an extended process for measuring spatial similarity between place graphs is suggested that consists of three steps: spatial relation classification, graph reconstruction, and iterative similarity scoring. After processing the steps,
the overall output is a matrix of similarity scores for the associated spatial objects. The similarity scores at each of the candidate nodes are calculated by performing the aggregation of the similarity of the associated neighbours according to their spatial relations.

**Spatial relation classification**

To measure the semantic similarity of the spatial relations between objects and their neighbours, the similarity between these relations in NL should be defined. Such NL relations have complex semantics (Schwering, 2007).

In this work it is assumed that semantically similar spatial relations can be mapped to a canonical finite set of relation terms. Therefore, a flexible and extendable classification table can capture these mappings, such as Table 10, in which, for example, ‘near’ and ‘nearby’ have been mapped to ‘around’ because of similar meaning.

**Table 10: The qualitative spatial relation classification**

<table>
<thead>
<tr>
<th>Implemented relations</th>
<th>NL relations</th>
</tr>
</thead>
<tbody>
<tr>
<td>center</td>
<td>center</td>
</tr>
<tr>
<td>north</td>
<td>north, northern, N</td>
</tr>
<tr>
<td>south</td>
<td>south, southern, S</td>
</tr>
<tr>
<td>east</td>
<td>east, eastern, E</td>
</tr>
<tr>
<td>west</td>
<td>west, western, W</td>
</tr>
<tr>
<td>north east</td>
<td>north east, NE</td>
</tr>
<tr>
<td>north west</td>
<td>north west, NW</td>
</tr>
<tr>
<td>south east</td>
<td>south east, SE</td>
</tr>
<tr>
<td>south west</td>
<td>south west, SW</td>
</tr>
<tr>
<td>left</td>
<td>left</td>
</tr>
<tr>
<td>right</td>
<td>right</td>
</tr>
<tr>
<td>front</td>
<td>front</td>
</tr>
<tr>
<td>back</td>
<td>back, behind</td>
</tr>
<tr>
<td>above (horizontally)</td>
<td>above, upper, top of, up</td>
</tr>
<tr>
<td>below (horizontally)</td>
<td>below, lower than, bottom of</td>
</tr>
<tr>
<td>under (vertically)</td>
<td>under, underneath</td>
</tr>
<tr>
<td>next</td>
<td>next, beside</td>
</tr>
<tr>
<td>inside</td>
<td>in, inside, into, within</td>
</tr>
<tr>
<td>outside</td>
<td>outside</td>
</tr>
<tr>
<td>around</td>
<td>near, nearby, adjacent</td>
</tr>
<tr>
<td>surround</td>
<td>surround</td>
</tr>
<tr>
<td>opposite</td>
<td>opposite, other direction from, other side of</td>
</tr>
</tbody>
</table>
Further, in order to be able to match cases like ‘A north of B’ in one graph and ‘B south of A’ in the other graph, the graphs are temporarily brought into a standardized form with a process described here.

The standardization process converts the semantically transformable edges into their representative reference forms. As shown in Figure 21, the transformable inverse spatial relations are classified in different groups through analysis of the candidate regions around a relatum $r$, in which a locatum $l$ can be placed. These candidate regions are based on cardinal zones. For example, ‘north’ and ‘south’ are classified in one group because ‘north’ and ‘south’ are transformable due to their inverse relation. Then, one of the spatial relations in each group is defined as the default representative reference. Relations such as ‘center’ with no transformable inverses, remain the same. With this process, every edge’s label and direction are represented in a standardized way.

![Figure 21: Candidate regions and representatives of spatial relations](image)

The classified and transformed relations of standardized graphs are only used for finding the corresponding objects between original graphs. For example, ‘B south of A’, just for the purpose of matching, is temporarily adjusted to ‘A north of B’ for matching purposes, according to Figure 21. Figure 22 shows a graph (left) and its temporarily adjusted version (right).

![Figure 22: A graph (left) and its temporarily adjusted graph (right)](image)
Iterative similarity scoring

Graph similarity scores are calculated then from the temporarily adjusted graphs. For matching two graphs, the similarity score at each node is calculated extending the similarity flooding algorithm (Melnik et al., 2002). In this approach, the PCG is derived considering the semantic similarity of spatial relations. Each pair of nodes in the PCG represents one possible mapping when they also have similar spatial relations with their neighbours. Each edge in the PCG shows the spatial relation of its pair.

Figure 23 shows a PCG generated from graphs A and B, which consists of all possible mapping pairs according to their similar relations. The PCG consists of three unconnected sub-graphs corresponding to the different mapping options. For example, consider the pair (‘Entrance to the Campus’, ‘Main South Entrance’). The middle nodes in the respective graphs have two ‘north’ edges as one is incoming in and the other is outgoing. Thus, ‘Entrance to the Campus’ in graph A and ‘Main South Entrance’ in B can be mapped to each other because they have the same relation with their neighbours in the respective graphs. The weights of the edges in the similarity propagation graph indicate how well the similarity of a given map pair propagates to its neighbours. These weights (called propagation coefficients) range from 0.0 to 1.0. Each edge makes an equal contribution of 1.0 to propagating similarities from a given mapped pair. For example, there is exactly one edge out of (‘Engineering Building-Main South Entrance’) in the propagation graph. In such case the weight of the edge is set to 1.0, which indicates that the similarity of ‘Engineering Building’ and ‘Main South Entrance’ contributes fully to that of ‘Entrance to the Campus’ and ‘Grattan Street’.

Figure 23: A pairwise connectivity graph from two standardized graphs A and B, and their spatial similarity via iterative similarity scoring
In the similarity propagation graph of Figure 23, the spatial similarity scores for all pairs have been calculated. For instance, the spatial similarity score of ‘Engineering Building-Engineering Building’ is initialized by an average value 1.0 of their string (1.0) and linguistic (1.0) similarities. Then, the spatial similarities of pairs are measured by propagating similarities of the neighbours iteratively. In the first iteration, the propagated spatial similarity of ‘Engineering Building-Engineering Building’ is 0.26 — calculated by multiplying the initial value (0.52) by the weight (0.5) of the incoming edge from its neighbour (‘Entrance to the Campus-Main South Entrance’). Thus, the aggregate spatial similarity of ‘Engineering Building-Engineering Building’ is 1.26, while the aggregate spatial similarity of ‘Entrance to the Campus-Main South Entrance’ is 2.52, which after the first iteration is the highest value. For normalization, each value is divided by the maximum value. In the second iteration, their spatial similarities are measured again for propagating the normalized similarity scores calculated from the first iteration in the similar way. The normalized similarity scores of ‘Engineering Building-Engineering Building’ and ‘Entrance to the Campus-Main South Entrance’ in the second iteration are 0.5 and 1.0 respectively. Since their spatial similarity scores in the first iteration are the same in the second iteration, the algorithm stops here.

These values indicate how well the nodes in graph A can be mapped onto nodes in graph B. The highest value ‘1.0’ indicates a given pair can be mapped perfectly according to the similarities of the associated neighbours in the respective graphs, while a value of ‘0.0’ indicates that the given mapped pair should not be mapped because there is no spatial similarity. The higher the values, the more similar their neighbours are.

As Algorithm 3 states, to sum up, a PCG is created considering all possible mapping pairs having similar spatial relations between two standardized graphs (Task 1). Initial similarity values of nodes are calculated using their average of string and linguistic similarities. The weight for each edge is calculated as 1.0 divided by the number of similar edges leaving from the same source to any destination node (Task 2). Then the similarity scores of all the nodes are measured and divided by the value of the node with the maximum value after each iteration. This computation is performed iteratively until the sum of the absolute differences between the current spatial similarity values and the next values is less than a fixed minimum residual. If the computation does not converge, it is terminated after some maximal number of iterations (Task 3).
To construct a composite place graph, the overall similarity between nodes, computed from the string, linguistic, and spatial similarities, can be expressed by Equation 4. $S_O$ is the overall similarity score, a weighted average ranging from 0.0 to 1.0. The corresponding candidate nodes are considered to refer to the same real world object when their similarity is higher than a threshold.

\[ S_O = W_T \ast S_T + W_L \ast S_L + W_S \ast S_S \]  

- $S_O$ = Overall similarity score ($0.0 \leq S_O \leq 1.0$)
- $S_T$ = Normalized string similarity score ($0.0 \leq S_T \leq 1.0$)
- $S_L$ = Normalized linguistic similarity score ($0.0 \leq S_L \leq 1.0$)
- $S_S$ = Normalized spatial similarity score ($0.0 \leq S_S \leq 1.0$)
- $W_T$ = Weight factor of the string similarity
- $W_L$ = Weight factor of the linguistic similarity
- $W_S$ = Weight factor of the spatial similarity
- $W_T + W_L + W_S = 1.0$

For instance, Figure 24 shows the overall similarity scores with equal weights for graphs A and B in Figure 22 according to Equation 4. Three pairs — (‘Engineering Building’–‘Engineering Building’), (‘Grattan Street’–‘Grattan Street’), (‘Entrance to the Campus’–‘Main South Entrance’) — have scores higher than 0.65 for overall similarity. The pairs (‘Engineering Building’–‘Engineering Building’) and (‘Grattan Street’–‘Grattan Street’) have 1.0 in both of string and linguistic similarity, and have 0.5 in spatial similarity. They have the same name and meaning linguistically, but only medium spatial similarity. In contrast, the pair of (‘Entrance to the Campus’–‘Main South Entrance’) has the highest spatial similarity (1.0), which means this pair has the same neighbours with the same relations. Thus, their overall similarity is relatively high (0.68) even if their string and linguistic similarities are just around 0.5 (comparably low). Note that balancing between the three similarity measures is required because geographic name (and type) ambiguity is prevalent in place descriptions, and only the embedding in a spatial configuration can resolve these ambiguities.

According to the overall similarity scores measured between two graphs, the graphs can be integrated into a composite graph: Nodes are merged if their similarity is above a chosen threshold, and their names, if different, are carried over as synonyms. Whatever is connected to these nodes before merging is adopted in the composite graph (Figure 24). Thus, a large number of small graphs, derived from individual place descriptions, can be merged into a large composite graph representing a database of human spatial knowledge.
Figure 24: Overall similarity scoring of graph A and B

5.4 EXPERIMENT

The approach was evaluated with a case study consisting of a set of NL place descriptions of the University of Melbourne’s Parkville campus, and additional descriptions of the campuses of two other universities. The assumption was that they may have similar names and similar structures — but refer to a different place. In total, 44 campus descriptions for the University of Melbourne, and one of each of the other campuses were collected. They were tested to assess the performance of the proposed overall similarity measure.

The threshold is the value used to determine the matching pairs, and it is the lowest value of similarity a pair can have for being identified as matching — referring to the same real world feature. The sensitivity\(^2\) and specificity\(^3\) of the threshold were tested over the range of 0.5 to 1.0 (Figure 25a), and were found optimal at 0.6 (the cutoff point when precision\(^4\) is 0.82, recall is 0.63).

In addition, a cumulative distribution curve was measured for analyzing the distribution of spatial similarity scores of correctly matched pairs (threshold=0.6), as shown in Figure 25b. The spatial similarity scores range from 0.15 to 1.0, while the average and standard deviation values of them are 0.54 and 0.29, respectively.

Therefore, a general threshold of 0.6 is applied, but require in addition that matches with scores 0.6 ≤ \(S_O\) < 0.7 have at least a significant support (\(S_S \geq 0.15\)) in form of spatial similarity. For instance,

\(^2\) The sensitivity (or the recall = true positives / (true positives + false negatives)) represents the proportion of positives that actually belong to the correct pairs.

\(^3\) The specificity (=true negatives / (true negatives + false positives)) is the proportion of negatives that are correctly identified.

\(^4\) The precision represents the number of correctly matched pairs (true positives) divided by the total number of pairs matched as belonging to the correct pairs (the sum of true positives and false positives).
Figure 26 shows a result of the graph matching for Graph #1 and Graph #2 (from Description #1 and #2, respectively).

The ground truth provides the synonyms of the spatial objects identified in the descriptions as shown in Table 11. In total, 81 unique objects were identified among the 44 campus descriptions. The spatial objects matched by the proposed matching process using equal individual similarity weights and a threshold of 0.6 are also shown with bold font. For example, ‘Alice Hoy’ in one description was also identified as ‘Alice Hoy Bldg’ or ‘Alice Hoy Centre’ by the human-generated ground truth, while ‘Alice Hoy’ and ‘Alice Hoy Bldg’ were matched in the results using the graph-based approach. The overall results of this experiment (with a fixed threshold of 0.6) are shown in Table 12, comparing the object pairs of the graph matching with the pairs of the human-generated ground truth. The results were calculated in terms of precision and recall. The highest values, 0.82 and 0.63 for precision and recall, respectively, appear in the case of equal weighing factors, i.e. $W_T=W_L=W_S=0.333$.

Table 11: Spatial objects (bold words) matched by the matching process

<table>
<thead>
<tr>
<th>Object names</th>
<th>Identical object names</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alice Hoy</td>
<td>Alice Hoy Bldg, Alice Hoy Centre</td>
</tr>
<tr>
<td>Architecture Building</td>
<td>Architecture School</td>
</tr>
<tr>
<td>Arts</td>
<td>Arts School, Arts West Building</td>
</tr>
<tr>
<td>Athletic Tracks</td>
<td>Sport Tracks, Sports Track, Sports Field, Sports Ground</td>
</tr>
<tr>
<td>Baillieu Library</td>
<td>Main Library</td>
</tr>
<tr>
<td>Baretto</td>
<td>Barretto</td>
</tr>
<tr>
<td>Biology Building</td>
<td>Bio Block</td>
</tr>
<tr>
<td>Botany</td>
<td>Botany School, Botany Building, Botanic Building</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>

Note: The ground truth was prepared based on human judgement.
In order to test the approach for matching different places, a description of each of the RMIT and the Monash Clayton campuses was added. The descriptions of the RMIT campus and the University of Melbourne campus include both references to (the same) ‘Swanston Street’ and ‘Central Business District (CBD)’. Only the description of the Monash Clayton campus does not overlap with the other campus descriptions. As a result of this test, the objects such as ‘Swanston Street’ and ‘CBD’ are matched correctly with the overall average scores higher than 0.7 between the Melbourne campus and the RMIT cam-

<table>
<thead>
<tr>
<th>Cases (Threshold: 0.6)</th>
<th>$W_T$</th>
<th>$W_L$</th>
<th>$W_S$</th>
<th>Precision</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equal weights for three similarities</td>
<td>0.3333</td>
<td>0.3333</td>
<td>0.3333</td>
<td>0.8225</td>
<td>0.6290</td>
</tr>
<tr>
<td>Only string similarity</td>
<td>1.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.7831</td>
<td>0.5882</td>
</tr>
<tr>
<td>Only linguistic similarity</td>
<td>0.0</td>
<td>1.0</td>
<td>0.0</td>
<td>0.8110</td>
<td>0.6018</td>
</tr>
<tr>
<td>Only spatial similarity</td>
<td>0.0</td>
<td>0.0</td>
<td>1.0</td>
<td>0.7465</td>
<td>0.2398</td>
</tr>
<tr>
<td>Both string and linguistic similarities</td>
<td>0.5</td>
<td>0.5</td>
<td>0.0</td>
<td>0.8036</td>
<td>0.6109</td>
</tr>
<tr>
<td>Both Linguistic and spatial similarities</td>
<td>0.0</td>
<td>0.5</td>
<td>0.5</td>
<td>0.8103</td>
<td>0.4751</td>
</tr>
<tr>
<td>Both string and spatial similarities</td>
<td>0.5</td>
<td>0.0</td>
<td>0.5</td>
<td>0.7963</td>
<td>0.3891</td>
</tr>
</tbody>
</table>

... ... ... ... ...

Figure 26: Result of the graph matching for graph #1 and graph #2
pus. However, the other objects such as ‘Library’ and ‘Shops’ that have the string (1.0) and linguistic similarity (1.0) and an overall average score 0.67 are not matched. This is due to having insufficient support by spatial similarity.

To sum up, the evaluation shows that the proposed feature similarity measure combining the string, linguistic, and spatial similarities with equal weights for matching various places is more reliable, with higher precision and recall than each similarity alone, or the combined similarity of any two of them.

5.5 Chapter Discussion and Summary

In place descriptions, people use different forms of object names. These are often expressed as various abbreviations, synonyms, and vernaculars. Thus, object names may not always appear in regular forms. In a case study with written descriptions, people often used shortenings and contractions of object types such as ‘Bldg.’ for ‘Building’, as well as initialisms of object names such as ‘SMAB’ for ‘Sidney Myer Asia Building’. These abbreviations result in significant challenges for string or linguistic matching. To properly compare names, the abbreviations that people commonly use can be processed by applying additional mappings. Heuristic rules for these mappings might be employed to aid in identifying equivalent names. In addition, object names can be compared in a number of combinations since the names often consist of different sets of words. For example, ‘Alice Hoy’ and ‘Alice Hoy Bldg’ are labels for the same object. To compare two sets of words, therefore, the maximum matching similarities between them should be considered.

The linguistic similarity measures require exact string matches with WordNet content. In order to deal with misspellings, string similarity can be introduced to relax the matching. However, some words, for example, street names, are not identified since they are not catalogued in WordNet. The total number of word pairs tried by linguistic matching is 35,209, while the number of cases replaced by string matching attempting to fit to catalogued words is 8,547 (around 24%). Generally, WordNet is better suited for types in aggregate place names than for the names themselves. Place descriptions are not always explicit whether a word is used as a name or as a type. As an alternative solution, state-of-the-art machine learning can be considered for enriching WordNet’s existing network with new lemmas and senses from resources such as Wiktionary.

5. String and linguistic matching alone are not enough: they do not capture the spatial semantics in relationships. In the case of the experiment using threshold 0.6, the precision and recall of the string matching are 0.78 and 0.59 respectively, and the linguistic matching

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5 https://en.wiktionary.org/
0.81 and 0.60, while for the spatial matching the values are 0.75 and 0.24. The precision and recall of the combination of any two of similarity measures are relatively low. However, the combination of string, linguistic, and spatial similarities shows the highest precision (0.82) and recall (0.63) compared to each of them. This result shows that considering spatial similarity is essential to avoid mismatches. An underlying assumption is that people will come up with similar descriptions when describing the same place. This assumption holds only so far, but has support from the notion of salience of geographic features (Winter and Richter, 2014). Thus, the spatial similarity measure between descriptions will play a key role for identifying spatial features.

With regards to different granularity levels in measuring spatial similarity, one important aspect of descriptions of spatial configurations is that a spatial environment can be described in terms of coarser or finer entities. Place descriptions include conceptual boundaries as well as complex objects with interior structures when some relations such as ‘inside’ are used. In the current stage, this research deals with such relations for measuring spatial similarity as shown in Table 10. In addition, the roles of spatial objects are identified as features on level 3 (building) and level 4 (street) of the granularity schema (Richter et al., 2013), since this research is focusing on spatial relations and features of a local environment.

Furthermore, the spatial similarity depends on the extraction of spatial relations from the source descriptions. In the experiment, the largest number of spatial relations extracted from one of the descriptions was 51, and the average number for each description was 18. Each place name had around two edges since the average number of relations for each node was 1.92. These figures show that individual places could have enough spatial relations for measuring their spatial similarity. As a result, the weight of spatial similarity could be distributed equally compared with the other weights. However, in general, it cannot be always expected to use dense place descriptions. Applicability of the spatial similarity measurement depends on the quality of place descriptions, or more precisely relies on how many spatial relations are provided in the descriptions.

Therefore, determining weights for measuring overall similarity depends on the quality of the corpus of descriptions. The lack of adequate spatial relational information may result in low precision and recall values. The reason is that a graph including many edges (spatial relations) between objects provides more information for graph matching than a sparser graph which does not include enough information in terms of spatial similarity. However, with regards to online repositories, place descriptions were harvested from Web pages such as Wikipedia. The generated composite place graph revealed that this approach is applicable and the number of the identified spatial re-
lations is sufficient to produce a reasonably connected graph. The graph contained 2,736 unique nodes, representing the unique place names identified, and 3,221 edges, representing the identified spatial relations between them.

Another important factor is how to determine the best threshold for getting the most of the matching pairs. Therefore, a trade-off between sensitivity and specificity can be considered. Furthermore, even if the overall average score of two compared features is 0.67 (string=1.0, linguistic=1.0, spatial=0.0), the features should not be matched, because the individual similarity values do not have sufficient support by spatial similarity. For example, there are common nouns used to refer to various places, especially when indicating the place’s function, such as ‘Library’. They are not the actual names of places such as ‘Melbourne City Library’. The ratio of such cases is around 22% with spatial similarity 0.0, which should not be matched. When these unspecific names are used in descriptions for different places, they should be distinguished for ideal matching.

To sum up, this chapter introduced a new approach for integrating spatial information extracted from multiple place descriptions. The approach is based on the graph matching process of measuring the overall feature similarity. It combines the string, linguistic, and spatial similarity of objects (nodes in a place graph) for this purpose. The core idea is that if two places from two place graphs have typographically and linguistically similar names, and if their neighbours are similar (their names and their connecting spatial relations), the places score high in overall similarity and can be matched.

The suggested iterative similarity scoring algorithm extends the classic similarity flooding algorithm. The extension allows computing node similarity scores via propagating the similarities of the associated neighbouring nodes, especially considering first- and higher-order neighbours. Furthermore, a spatial relation classification is introduced for the canonization of NL expressions of spatial relations, and a standardization process is introduced that enables edge matching for semantically identical relationships.

The linguistic similarity measure based on WordNet shows relatively strong word semantic similarity, but some words (around 24%) could not be identified. Alternatively, these words were processed partially by using the string similarity measure. Another issue, comparing two place names of different numbers of words, has been solved by assigning the sum with maximal value to the edges of weighted bipartite graphs.

This work contributes to the improvement of feature matching methods for organizing and integrating human spatial knowledge by exploring graph matching methods of the graphs produced from multiple place descriptions. Side products include identifying synonyms for place names of matching nodes.
Algorithm 3 Spatial similarity measure

1: procedure MeasureSpatialSimilarity(StdG_A, StdG_B) ⇒ Two standardized place graphs; StdG_A and StdG_B.
2: (Task 1) create a pairwise connectivity graph PCG
3: for each edge E_A in StdG_A do
4:    for each edge E_B in StdG_B do
5:        if isSimilarSpatialRelations(E_A, E_B) == TRUE then
6:            ⇒ create a source node SrcN_P of PCG, and set up the initial weight
7:            TypoSim = paramStringSimilarity(SrcN_A, SrcN_B)
8:            LingSim = getLinguisticSimilarity(SrcN_A, SrcN_B)
9:            InitWeight = (TypoSim + LingSim) / 2.0
10:            SrcN_P.setWeight(InitWeight)
11:            ⇒ add the new source and target nodes to PCG, and connect their edges
12:            PCG.addNode(SrcN_P), PCG.addNode(TrgN_P)
13:            PCG.addEdge(SrcN_P, TrgN_P), PCG.addEdge(TrgN_P, SrcN_P)
14:        end if
15:    end for
16: end for
17: (Task 2) initialize the weight for each edge of PCG
18: for each node N_P in PCG do
19:    for each outgoing edge E_P of N_P do
20:        Count = PCG.getOutgoingsCount(N_P)
21:        E_P.setWeight((1.0 / Count))
22:    end for
23: end for
24: (Task 3) measure the spatial similarities of all possible mapping pairs
25: Iteration=0
26: while Iteration < MaxIteration && Residual > MinResidual do
27: SpatialSim = 0.0, MaxSim=0.0, Residual=0.0
28: for each node N_P in PCG do
29:    for each edge E_P in PCG.getIncomingEdgesOf(N_P) do
30:        SpatialSim += (E_P.getWeight() * PCG.getSourceNode(E_P).getWeight())
31:    end for
32: end for
33: NodeSim = N_P.getWeight() + SpatialSim
34: N_P.setNextWeight(NodeSim)
35: MaxSim = Max(MaxSim, NodeSim) ⇒ find the maximum similarity value
36: end for
37: for each node N_P in PCG do
38:    NextWeight = N_P.getNextWeight() / MaxSim
39:    Residual += Abs(N_P.getWeight() - NextWeight)
40:    N_P.setWeight(NextWeight) ⇒ set the normalized weight of each node
41: end for
42: Iteration++
43: end while
44: end procedure
The harvested large corpora of place descriptions, as introduced in Chapter 4, provide abundant human spatial knowledge, different from the geometry-based information stored in current GIS. These place descriptions, used in everyday communication, frequently refer to landmarks. The spatial knowledge contained in the harvested place descriptions provides references to spatial objects, and the (mostly) qualitative spatial relations among them. The knowledge, different from the geometry-based information stored in current GIS, is represented in a composite place graph after the matching process, as introduced in Chapter 5.

Based on the composite place graph, this chapter studies the way of extracting salient objects as landmarks from these composite place graphs. A model for extracting landmarks from web-harvested place descriptions is presented, considering the landmark’s cognitive significance. The model allows landmarks to be extracted according to different contexts via web harvesting and text classification methods. In addition, an implementation based on this model is used to extract context-based landmarks for a target area — Melbourne in Australia.

6.1 INTRODUCTION

Landmarks are cognitively salient spatial objects in terms of prominence and distinctiveness, used in constructing mental images of places Winter and Richter (2014). The cognitive significance of landmarks is evident from previous research where landmarks are studied as external reference points Lynch (1960), salient anchor points Couclelis et al. (1987), or as aid to locate other, less prominent features Sadalla et al. (1980). Due to their distinct characteristics, people use landmarks frequently in their own orientation, navigating and wayfinding, and thus, references to landmarks appear in NL place and route descriptions.

Identifying landmarks automatically for the use in computers involves tedious procedures; for a review see Winter and Richter (2014). Most existing landmark extraction methods rely on identifying visual, structural, and cognitive characteristics of objects. This research, in contrast, considers information available in NL descriptions referring to landmarks, rather than observing their characteristics. In order to study a critical mass of data, this chapter concentrates on place descriptions harvested from web documents. The spatial knowledge
contained in these documents can be extracted with text analysis techniques, in the form of references to spatial objects, and the (mostly) qualitative spatial relations among them. Since landmarks are generally context dependent, the proposed model also groups landmarks in different (conversational) contexts.

The proposed model, comprises four main phases, namely: a) web harvesting of place descriptions, b) text classification, c) modeling of knowledge about places as extracted from descriptions, and d) landmark identification in these place models. In (a), the approach of harvesting place descriptions from the Web (see Chapter 4 for more detail) provides an efficient strategy in harvesting relevant web pages including place descriptions related to a particular environment, and extracting spatial information from the descriptions via NLP. In (b), established methods can be applied Loh (2008); Manning et al. (2008). In (c), modeling of spatial information is based on the similarity matching process (introduced in Chapter 5) that relies on the comparison of string, linguistic and spatial similarities between identified places. The matching process uses individual place descriptions as an input, and produces a composite place model with qualitative spatial relations from the descriptions. Therefore, the contribution of this chapter is a model for landmark identification (d) in place models in different contexts. The proposed landmark extraction model is fully scalable in spatial coverage, as well as spatial granularity, paving the way toward automated identification of cognitively salient features as landmarks. In this research, the proposed model has been implemented and tested fully.

### 6.2 Landmark Extraction Model

In order to extract landmarks, place descriptions are harvested from the web by using the web mining approach introduced in Chapter 4. The descriptions are categorized into environment, travel, business, and other descriptions. The categories depend on the conversational contexts of the data sources. In an experiment of this research, Wikipedia pages, business pages and tourist sites have been used.

The descriptions of each category are transformed into multiple sets of triplets, using the NL parsing (Khan et al., 2013; Liu et al., 2014). A triplet consists of three elements $<l, s, r>$: an object to be located (a locatum $l$), a reference object (a relatum $r$), and the directed spatial relation $s$ between them. The NL parser provides approximately 75% precision in a fully automated procedure. Due to the limitations of the current NLP, the extracted triplets also include non-locative expressions. Therefore, the triplets have been further filtered by a set of rules based on the more frequent exceptions found in this experiment, such as temporal expressions, event names, composite locative expressions, and personal pronouns in locata or relata.
Locata and relata become the sets of nodes $V$ of a place graph $G$, and the relations the set of edges $E$. Each individual description forms a place graph, and separate graphs of the same place can be merged into a composite one by identifying corresponding nodes using similarity measures, as described in Chapter 5.

The proposed landmark extraction model (LEM) (Figure 27), works on the composite graphs of any of the four place description categories, providing contextualized landmarks. Such a composite graph provides a place model abstracting collective human spatial knowledge, and is capable of signifying landmark candidates. Three measures are calculated from a composite place graph and used to identify landmark candidates: reference, familiarity, and betweenness. These measures are introduced in the following paragraphs.

Reference significance.

Landmarks are used in place descriptions as reference features that help to localize other features. This characteristic is revealed in the place graph by the in-degree centrality of a node. The in-degree corresponds to the number of times people used a reference to the specific node to locate other features around. A high in-degree implies that many people perceive this feature as salient. After normalization by dividing the in-degree of each node by the highest in-degree centrality $H^{-}$ in $G$, the reference significance $S_{R}$ of each node ranges between 0.0 and 1.0 (Equation 5).

$$S_{R}(v) = \frac{\text{deg}^{-}(v)}{H^{-}}$$

For instance, the in-degree sum of the node ‘QV’ is 17, as seen in the graph of Figure 28. According to Equation 5, the reference significance of ‘QV’ is 1.0 since the highest in-degree centrality is 17, while the reference significances of ‘Lonsdale Street’ and ‘State Library of Victoria’ are 0.29 which is the second highest value.

Familiarity significance.

Landmarks are cognitively salient spatial features known by smaller or larger communities. Thus, a generalization of reference significance, the familiarity significance, looks at the total occurrence of a spatial feature, or its node degree. Accordingly, familiarity significance is the degree normalized by the highest degree $H$ in $G$ (Equation 6).

$$S_{F}(v) = \frac{\text{deg}(v)}{H}$$
Landmarks may have structural significance due to their prominent position among their neighbors. Therefore, betweenness centrality is considered as an additional indicator of a node’s significance. Betweenness centrality (Equation 7) is equal to the number of the shortest paths from all nodes to all others that pass through that node. $P_{st}$
is the total number of the shortest paths from node $s$ to node $t$, and $P_{st}(v)$ is the number of those paths that pass through $v$.

$$B(v) = \sum_{s \neq v \neq t} \frac{P_{st}(v)}{P_{st}} \tag{7}$$

The betweenness significance of a node is measured by normalizing each betweenness centrality with the maximum value $K = \max(B_C(v))$ in the place graph (Equation 8).

$$S_C(v) = \frac{B_C(v)}{K} \tag{8}$$

This method produces a relative ranking of candidate landmarks according to their perceived salience (in their context). Any measure greater than 0 is considered to indicate some landmarkness (both reference and familiarity significance can be 0).

6.3 Experiment

An experiment was conducted to test the proposed model for extracting landmarks from place descriptions, as well for discussing the characteristics of the candidate landmarks, and the differences among context-based landmarks. The targeted area, the city of Melbourne, is the second most populous city in Australia. It also rates
Figure 29: Distribution of the harvested start URLs and place descriptions for Melbourne

high in education, entertainment, health care, research and development, tourism, and sport. It is, thus, related with place descriptions in a variety of contexts. In order to harvest such place descriptions the following data sources were used: WikiMapia, Wikipedia, official sites of businesses or institutions, tourist sites, and blogs. The starting URLs of places were collected using the WikiMapia place search APIs. Figure 29 shows the locations of the URLs on a map. Starting from these URLs, web crawling reached 19,125 web pages and the number of texts extracted by web scraping is 16,527. From these texts, 2,911 sets of triplets were identified using NLP, i.e., maximal 17.6% of these texts contained a recognized place description.

6.3.1 Place description classification

For accommodating different contexts, the harvested descriptions are classified into four categories: environment, business, travel and other. The categories are deliberate choices, as discovered in the data sources. A decision tree in WEKA was chosen for the descriptions classification Hall et al. (2009), because WEKA has been widely adopted by the text mining communities. A random sample of the place descriptions was selected and manually classified into the four categories. This sample (around 30%, or 808 place descriptions) was then used for training and testing. In the evaluation on the training data set, around 95% of place descriptions were correctly classified, as shown in Table 13. The detailed accuracy and the confusion matrix for each category are shown in Tables 14 and 15, respectively. Thus, a large set of place descriptions with known categories were used to train
the classifier, which was subsequently used to classify all of the harvested place descriptions.

Table 13: Evaluation of training set for text classification

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<tbody>
<tr>
<td>Correctly classified descriptions</td>
<td>770 (95.297%)</td>
</tr>
<tr>
<td>Incorrectly classified descriptions</td>
<td>38 (4.703%)</td>
</tr>
<tr>
<td>Total number of descriptions</td>
<td>808</td>
</tr>
</tbody>
</table>

Table 14: Detailed accuracy for each category

<table>
<thead>
<tr>
<th>Class</th>
<th>TP(^1)</th>
<th>FP(^2)</th>
<th>Precision(^3)</th>
<th>Recall(^4)</th>
<th>F(^5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Environment</td>
<td>0.968</td>
<td>0.037</td>
<td>0.963</td>
<td>0.968</td>
<td>0.966</td>
</tr>
<tr>
<td>Business</td>
<td>0.963</td>
<td>0.023</td>
<td>0.947</td>
<td>0.963</td>
<td>0.955</td>
</tr>
<tr>
<td>Travel</td>
<td>0.924</td>
<td>0.007</td>
<td>0.936</td>
<td>0.924</td>
<td>0.930</td>
</tr>
<tr>
<td>Other</td>
<td>0.875</td>
<td>0.007</td>
<td>0.933</td>
<td>0.875</td>
<td>0.903</td>
</tr>
</tbody>
</table>

Table 15: Confusion matrix for each category

<table>
<thead>
<tr>
<th>Class</th>
<th>Environment</th>
<th>Business</th>
<th>Travel</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>Environment</td>
<td>394</td>
<td>10</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Business</td>
<td>8</td>
<td>233</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Travel</td>
<td>1</td>
<td>1</td>
<td>73</td>
<td>4</td>
</tr>
<tr>
<td>Other</td>
<td>6</td>
<td>2</td>
<td>2</td>
<td>70</td>
</tr>
</tbody>
</table>

6.3.2 Landmark extraction with different contexts

1,201 place descriptions, mainly from Wikipedia, were classified as *environment*. They included information such as locations of public parks, environmental layouts, and history facts. The descriptions in the environment category tend to show relatively more public and broad spatial information for a given environment, representing people’s local knowledge.

Figure 30 shows the composite environment place graph for Melbourne generated from the descriptions harvested from the web. This graph contains 1,403 unique nodes, representing the unique place names identified, and 1,684 edges, representing the identified spatial relations between them. Figure 31 shows the landmarks extracted by calculating their significance measures as well as their word representations accordingly.

In the *business* category, a relatively large number (1,111) of place descriptions for Melbourne were found, mostly from Melbourne’s Central Business District (Melbourne CBD). As the place descrip-
Figure 30: Place graph of the place descriptions in the environment category for Melbourne

Figure 31: Landmarks extracted from environment classified place descriptions for Melbourne

...tions are related to business, the web sites usually provide human-generated place descriptions introducing the location of the business or institution, frequently combined with sketch maps or linked online maps such as Google Maps. In addition, the harvested descriptions in the business category provide not only place names with high familiarity (for orientation) but also typically official names such as address elements.
In the travel category a smaller number (218) of place descriptions were found, mainly on commercial tour sites and blogs. The descriptions were typically informing travelers about popular visiting spots, including cafes or restaurants, and their locations. Accordingly, these descriptions show a tendency for tour-oriented spatial information, and the landmarks extracted from the travel descriptions show primarily salient places for traveling or touring as well as specific tour spots.

### 6.4 Chapter Discussion and Summary

This chapter presented a model that supports an automatic method of extracting landmarks from unrestricted NL place descriptions. The implemented LEM has been tested in this experiment built around harvested place descriptions for Melbourne. These tests show that the LEM can robustly extract landmarks from a large number of complex place descriptions on the web, and within specific conversational contexts. The LEM accommodates different contexts in the classified text categories so that context-based landmarks are identified accordingly, using their reference, familiarity, and centrality significance. The significance scores range from 0.0 to 1.0 so that landmarks can be ranked according to their significance scores.

The computational complexity of the LEM for measuring the reference or familiarity significances is equal to the number of operations of calculating in-degree and out-degree of each node in a place graph, since it is an unweighted directed graph. The number of operations is \(O(n)\), where \(n\) is the number of nodes. In addition, the complexity of calculating betweenness centrality is \(O(nm)\), where \(m\) is the number of edges, which is linear with the size of the input. Therefore, the feasibility of the LEM is related to the size of a composite place graph.

Thus, in this experiment, the LEM appears feasible for a large place graph, such as the one provided in the example for Greater Melbourne. Moreover, this model’s running time can also be reduced using advanced technology of graph databases such as Neo4J\(^6\). For measuring betweenness significance, in particular, considering a certain threshold of spatial buffer or other factors such as a fixed depth of connectivity in the place graph may result in biased measures, since the entire neighbours connected to a place cannot be considered. However, reducing the computational complexity is efficient in dense cities.

In LEM, Reference significance reveals places as landmarks which help to identify the location of other features, i.e., form anchor points in individual cognitive representations. Familiarity reveals prominent places, which are shared knowledge among many people and used in

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\(6\) www.neo4j.com
a variety of ways in place descriptions. Centrality significance reveals places at prominent positions within a place graph.

As shown in Table 16, ‘Melbourne CBD’ was identified as a landmark with the highest reference and familiarity significance in the category of environment, and the second highest betweenness significance. It is a factual landmark and a well-known district of Greater Melbourne, with a daytime population of one million people. In the business context, ‘Docklands’ was ranked on top, in accordance with the fact that it includes a large number of business and government offices. In addition, the landmarks extracted from the place descriptions include well-known streets for business shops and offices such as ‘Elizabeth Street’ and ‘St Kilda Road’, and government offices such as ‘Melbourne Town Hall’. In the travel context, ‘Melbourne Zoo’ ranked highest and ‘Queen Victoria Market’ was the second highest since they are frequently visited places by tourists. The study of the landmarks extracted by LEM provides evidence that the model accommodates different contexts according to the classified categories.
Table 16: Top 10 context-specific landmarks in Melbourne according to their reference, familiarity, and betweenness significances

<table>
<thead>
<tr>
<th>Reference significance</th>
<th>Rank</th>
<th>Environment</th>
<th>Business</th>
<th>Travel</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>Melbourne CBD</td>
<td>Docklands</td>
<td>Melbourne Zoo</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>Flinders Street</td>
<td>Etihad Stadium</td>
<td>Queen Victoria Market</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>Flinders Street Station</td>
<td>St Kilda Road</td>
<td>Arts Centre</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>Yarra River</td>
<td>Federation Square</td>
<td>Elizabeth Street</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>Swanston Street</td>
<td>Melbourne Town Hall</td>
<td>Victoria Street</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>Crown Casino</td>
<td>Arts Centre</td>
<td>Healesville Sanctuary</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>Docklands</td>
<td>Elizabeth Street</td>
<td>Yarra Valley</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>Bourke Street</td>
<td>Dockers Street Station</td>
<td>Werribee Open Range Zoo</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>East Melbourne</td>
<td>City Road</td>
<td>Elizabeth Street</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>North Melbourne</td>
<td>Government House</td>
<td>Melbourne CBD</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Familiarity significance</th>
<th>Rank</th>
<th>Environment</th>
<th>Business</th>
<th>Travel</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>Melbourne CBD</td>
<td>Docklands</td>
<td>Melbourne CBD</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>Docklands</td>
<td>Arts Centre</td>
<td>Elizabeth Street</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>Flinders Street</td>
<td>Federation Square</td>
<td>Croissant Des Halles</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>Flinders Street Station</td>
<td>Etihad Stadium</td>
<td>Melbourne Zoo</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>Yarra River</td>
<td>Melbourne Town Hall</td>
<td>Queen Victoria Market</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>East Melbourne</td>
<td>Elizabeth Street</td>
<td>Geelong</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>Melbourne Cricket Ground</td>
<td>Dockers Street Station</td>
<td>Victoria Street</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>Swanston Street</td>
<td>St Kilda Road</td>
<td>Victoria Street Shops</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>Crown Casino</td>
<td>Healesville Sanctuary</td>
<td>Arts Centre</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>Bourke Street</td>
<td>Melbourne CBD</td>
<td>Yarra Valley</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Betweenness significance</th>
<th>Rank</th>
<th>Environment</th>
<th>Business</th>
<th>Travel</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>Parkville</td>
<td>Docklands</td>
<td>Melbourne CBD</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>Melbourne CBD</td>
<td>Southbank</td>
<td>Elizabeth Street</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>Flinders Street Station</td>
<td>Melbourne CBD</td>
<td>Queen Victoria Market</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>Bourke Street</td>
<td>St Kilda Road</td>
<td>Geelong</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>Yarra River</td>
<td>Kavanagh Street</td>
<td>Victoria Street</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>Melbourne Cricket Ground</td>
<td>Victoria Street</td>
<td>Melbourne Zoo</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>North Melbourne</td>
<td>Bourke Street</td>
<td>Etihad Stadium</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>Southbank</td>
<td>Arts Centre</td>
<td>Croissant Des Halles</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>Docklands</td>
<td>Etihad Stadium</td>
<td>Victoria Street Shops</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>Royal Park</td>
<td>Sturt Street</td>
<td>Arts Centre</td>
</tr>
</tbody>
</table>
DISCUSSION

Place descriptions provide a rich source of place knowledge that is complementary to the knowledge found in current GISs. However, as the major challenges of this research have been identified in Chapter 1, NL place descriptions are flexible, potentially vernacular and ambiguous descriptions of places that are not gazetteered in general. Spatial relations in the descriptions are mostly qualitative such as the relation ‘near’.

In this research, NL place descriptions have been used to build place knowledge in terms of place graphs. The main components in the place graph are places and their spatial relations. A new fully-automated mechanism has been presented for harvesting, parsing, interpreting, and integrating place descriptions by using current existing NLP. In addition to that, this research has demonstrated capabilities to construct place graphs from spatial information extracted from place descriptions, as well as to integrate them into the place knowledge-based database via the presented matching method. Apart from the construction of place knowledge, the LEM has been proposed as an effort to utilize the knowledge. The LEM has demonstrated how to extract landmarks from the place knowledge automatically. The extracted landmarks revealed cognitively salient places that people refer to describe their environments or locate other places.

The scientific cores of this research in studying places in GIScience from place descriptions to landmarks lie in: a) the understanding how to process NL place descriptions in terms of the extraction and integration of spatial information, b) the improvement of matching ambiguous place names between multiple descriptions by considering the spatial relations between places, c) the automated approach of drawing sketch maps based on cognitively motivated heuristics to support human-machine interaction, and d) the landmark extraction model based on the place knowledge.

In the following topics, more details will be discussed with the developed approaches and the achieved results, regarding the research objectives outlined in the introduction of this thesis. The scientific relevance and significances of this research will also be considered. In addition, the potential operationalization and future applicability of the developed methods will be discussed.
In order to interpret place descriptions, this thesis firstly investigated the locative expressions of place descriptions in terms of place names and their spatial relations. The experiments of applying the existing NLP method Khan et al. (2013); Liu et al. (2014) for the spatial information extraction from place descriptions have revealed that currently the automated NL parsing shows reliable outcomes, i.e., approximately 75% precision (Khan et al., 2013). Therefore, the spatial information could be extracted automatically from NL place descriptions.

The presented methods were developed for NL place descriptions. The methods were evaluated for outdoor and large scale environments such as a campus or a city. However, the methods can also be applied to spatial descriptions for indoor environments, since similar locative expressions including spatial objects and qualitative spatial relations can be observed. For example, the locative expressions can be observed in the form of paths, rooms and their spatial relations in a building, including their orientation, relative distances and relative positions. Moreover, the methods can be used in other kinds of linguistic spatial descriptions such as news articles. Thus, considering these applicabilities of the proposed methods will be worthwhile.

Drawing sketch maps from NL place descriptions

The place descriptions externalize relevant parts of mental spatial representations about a specific environment such as a campus. With regards to the mental spatial representations, this thesis has addressed an automatic procedure for drawing a sketch map from the spatial information extracted from a place description. The presented sketch map drawing algorithms are distinguished from other approaches because of its cognitively motivated heuristics, such as a sequential and hierarchical drawing process with human sketching preferences, therefore, resembling people’s process of dealing with underspecified information and conflict resolution.

As a potential use has been illustrated in Chapter 3, the presented approach generated a plausible sketch map from the emergency call description. The produced sketch map could be overlaid onto the map for assisting the call operators in dispatching help to the appropriate place. Moreover, this research provides the way of depicting qualitative spatial information with the help of cognitively motivated heuristics, which would be useful to produce sketch maps from qualitative scene descriptions for visualization of QSR tools such as SparQ (Wolter and Wallgrün, 2012). The drawing approach could also support advances in the establishment of a standard annotation scheme for precisely parsing and interpreting place descriptions such as the
The results of the sketch map drawing algorithm have raised some important questions requiring further investigation. When multiple descriptions of a place are considered, for example, more issues such as different semantics of spatial objects, combined reference frames, or ambiguous place names have to be considered, as well as the differences in individual cognitive maps. The issues would be interesting to investigate whether the combination of different descriptions of the same place can derive a plausible sketch map of collective awareness of a place. Moreover, the integration of gazetteers (geographic name databases) could be considered in the sketch map drawing procedure. Even if only a few of the references in a place description are authoritative (gazetteered) names the geographic coordinates coming with a gazetteered entry will further support the orientation and scaling of sketches, and allow a general georeferencing.

Harvesting large corpora of place descriptions from the Web

The web harvesting method introduced in Chapter 4 allows collecting large corpora of natural language place descriptions through user-generated content. The harvested place descriptions for the target environments contained a lot of user-generated place information such as Wikipedia and Wikimapia, and other place descriptions related to locations of companies, shops, and restaurants. In addition to that, tourist sites and blogs were also discovered to include popular places and attractions, as well as individual interests.

Therefore, the great potential of web-sourced data which provides human spatial knowledge could be demonstrated by the experimental tasks of this thesis. The results show that the implemented method provides an efficient way of harvesting place descriptions for a target environment from the web and a strategy of generating place graphs from spatial information extracted from the descriptions via NLP. The place descriptions also reaffirmed that most people prefer to use mostly qualitative spatial relations rather than quantitative ones.

Integrating spatial information extracted from place descriptions

For integrating spatial information extracted from the corpora, the approach of matching place names between multiple descriptions was developed as introduced in Chapter 5. The matching process is based on the spatial feature similarity measure, which considers a combination of string, linguistic, and spatial similarities. It provides an appropriate method for determining matching spatial objects, as these are

1 https://sites.google.com/site/wikiisospace/
The proposed method is flexible and accommodates different types of place descriptions, such as web documents, instant text messages and texts of social media allowing the complexity of comparing unrestricted object names, the complexity of qualitative spatial relations, and the limitations of each of the similarity measures.

By taking the spatial relations between places in a description into consideration, the presented similarity matching approach works for places that are not included in traditional gazetteers, while most of the existing approaches (i.e. Amitay et al., 2004; McKenzie et al., 2014; Scheffler et al., 2012) do not. In fact, the collected corpora show majority of non-gazetteered places. In addition, traditional GIR is limited to globally prominent places (Janowicz et al., 2011), but this approach is not based on frequency, but takes individual knowledge and relates it to other individual knowledge. Moreover, a well-established method of toponym disambiguation used in the process of toponym geocoding also takes account of co-occurring place names, which can be regarded as analogous to, but less precise than the use of spatial relations. Therefore, the presented matching approach contributes to the improvement of feature matching methods for dealing with spatial semantics, or in general, to spatial knowledge extraction from place descriptions. The main novel contribution is the idea of using qualitative spatial relations extracted from the source text.

Applicability of the spatial similarity measurement depends on the quality of place descriptions, and more precisely relies on the number of spatial relations in the descriptions. In general, we cannot always expect that dense place descriptions are available. Poorer spatial relational information in descriptions results in lower precision and recall values. However, with regards to online repositories, the place descriptions harvested from web pages such as Wikipedia in this experiment, generated the composite place graph. The experiment demonstrated that the matching approach is applicable and the number of the identified spatial relations is sufficient to produce a reasonably connected graph.

An integration of spatial information based on place descriptions could provide a knowledge graph (Franz et al., 2005; Nurdiati and Hoede, 2008; Sowa, 1984), opening the door for a plethora of future applications, from place-based GIS, to enriching current gazetteers (Keßler et al., 2009; Twaroch et al., 2008; Vasardani et al., 2013b). The knowledge could improve GIR based on place descriptions, which is an important field of current research with many open research challenges such as vague geographic terminology (Jones and Purves, 2008) and uncertainties of the position and the vagueness of the extent (Vasardani and Winter, 2015). In addition, it could support in advancing the development of intelligent tools interacting intuitively
with computers and location-based technologies such as wayfinding services (Duckham et al., 2010; Winter, 2003).

Extracting landmarks from place descriptions

As introduced in Chapter 6, the developed LEM supports a fully automatic procedure toward extracting landmarks from unrestricted NL place descriptions, as they reflect human spatial knowledge. The LEM provides a mechanism for place graphs construction, flexible enough to deal with underspecified NL expressions. The landmark extraction from these place graphs is based on three significance measures (reference, familiarity, and betweenness) from network topology.

Reference significance in the experiment revealed places as landmarks, which help to identify the location of other features, i.e., form anchor points in individual cognitive representations. Familiarity revealed just prominent places, which are shared knowledge of many people and used in any way in place descriptions. Betweenness significance revealed places on prominent positions within a place graph. The extracted landmarks were so far not distinguished clearly for their particular significance, which needs to be further investigated in future work.

The results of the implemented LEM show that the LEM can robustly extract landmarks from a large number of complex place descriptions on the web. Therefore, the LEM could exploit the utility of large amount of contents that could be used to extract landmarks even at rural regions. Moreover, the LEM from externalized human spatial knowledge identifies landmarks that people perceive and use frequently as prominent places, or as spatial reference to locate other objects in an environment. A key feature of this model is that it provides a wide range of place categories, unlike other landmark identification models that focus on buildings.

The LEM uses a composite place graph constructed from place descriptions within one text class. The place graph presents a feasible and reliable structure to store and manage abundant place names, including synonyms, and the spatial relations between the named places. It allows combining and updating the changes of place descriptions so that the model can reflect the recent updates about places seamlessly.

Lastly, the LEM could be applicable for place descriptions about indoor environments, and also support automatic selection of landmarks for navigation guidance (Zhu and Karimi, 2015), and routing instructions with landmarks (Duckham et al., 2010; Raubal and Winter, 2002). These applicabilities of the LEM would be worthwhile.
This thesis has addressed the efficient strategy of harvesting, processing, integrating, and utilizing spatial information from NL place descriptions. With regards to the objectives of this research, the thesis has developed the fully-automatic approaches in order to overcome the major challenges identified in Chapter 1: interpreting NL place descriptions, representing sketch maps based on place descriptions, harvesting place descriptions, resolving ambiguous place names and qualitative spatial relations, and extracting cognitively salient spatial objects as landmarks. The developed approaches have been fully tested to support the hypothesis outlined in Section 1.2.

Major results and findings

The developed approaches have been distinguished from existing methods, as the differences have been pointed out in Chapter 2. The major results and findings are presented as follows:

• **Modeling spatial information in place descriptions**: the descriptions are parsed via NLP in order to extract spatial information. The NLP extracts a set of spatial triplets through analyzing the locative expressions found in a place description. Then, each description is represented as a place graph in terms of place names and qualitative spatial relations. The study shows that place graphs can represent a feasible and reliable structure to store and manage abundant place names and their spatial relations. The place graphs can be used in advanced applications of place-based GISs, supporting a place knowledge that is complementary to the knowledge found in current GISs.

• **Constructing sketch maps from place descriptions**: the sketch map drawing approach introduced in Chapter 3 is based on cognitively motivated heuristics, such as a sequential and hierarchical drawing process with human sketching preferences. Therefore, the approach allows resembling people’s process of dealing with underspecified information and conflict resolution. The study has affirmed that the approach can generate sketch maps which are highly similar to human generated sketch maps in terms of object and relational similarities. In addition, the approach does not rely on the use of additional knowledge sources. As an application domain such as emergency call services is illustrated in Figure 14, therefore, the sketch map could be used...
to assist the call operators dispatching help to the appropriate place.

- **Integrating spatial information from large corpora:** the web-harvesting approach introduced in Chapter 4 collects large corpora of place descriptions for a target environment. The harvested place descriptions are textual type and written in NL. It is difficult to integrate because spatial information extracted from individual descriptions can be for any place, and include various abbreviations, synonyms, vernaculars and qualitative spatial relations. To overcome these difficulties, the new approach of integrating spatial information has been addressed in Chapter 5. The approach is based on the graph matching process of considering string, linguistic, and spatial similarities between identified places. The study shows that the performance of this process exceeds current toponym resolution by coping with non-gazetteered places.

- **Identifying context-based landmarks from the integrated spatial information:** the LEM introduced in Chapter 6 identifies landmarks that people perceive and use frequently as prominent features, or as spatial reference to locate other objects in an environment. A key characteristic of this model is that it provides a wide range of place categories, unlike other landmark identification models that focus on buildings. The LEM also identifies landmarks according to different conversational contexts. Furthermore, it is scalable and can be developed into an automated workflow with other GISs.

**Evaluation of hypothesis**

Returning to the hypothesis, it is now proven that "the developed model can support a fully automatic procedure towards extracting context-based landmarks from a large corpus of place descriptions." Throughout the experiments and evaluations of the developed approaches from Chapter 3 to Chapter 6, the hypothesis of this thesis has been proven. In addition, the following are answers to the research questions outlined in the introduction of this thesis.

- Spatial information extracted from an individual place description can be modelled as a place graph. A place graph can also be translated into a sketch map automatically.  
  » The development of the presented place graph construction and dynamic sketch map drawing algorithms have demonstrated that the presented approaches are feasible and robust for constructing place graphs, as well as translating a sketch map from a place description automatically.
Place descriptions harvested from the web are a rich source of human spatial knowledge. The developed web harvesting approach has been used to harvest large corpora of place descriptions. The results of experiments have demonstrated that the place descriptions are a rich source of user-generated place information regarding locations of companies, shops, and restaurants. Tourist sites and blogs have also been discovered, including popular places and attractions, as well as individual interests.

A large corpus of web-harvested place descriptions can be harvested and integrated into a knowledge database, and ambiguous place names from multiple descriptions in NL can be matched. The presented spatial similarity matching approach has been fully implemented and tested with the harvested place descriptions from the web. The performance of this process has been demonstrated, exceeding current toponym resolution by coping with non-gazetteered places. In addition, the results have affirmed that exploring spatial semantics (the given spatial relationships) with other spatial features is needed to resolve ambiguous or synonymous place names from place descriptions. The generated composite place graph has revealed that the approach is applicable and the number of the identified spatial relations is sufficient to produce a reasonably connected graph.

A composite place graph provides a place-based knowledge, abstracting collective human spatial knowledge, and capable of signifying landmark candidates. Three properties can be calculated from a composite place graph and used to identify landmark candidates: reference, familiarity, and betweenness. The presented LEM has been demonstrated to identify landmarks based on the composite place graph, considering reference, familiarity, and betweenness significances. The landmarks have been distinguished according to the different contextual views of place descriptions. The results also showed their heterogeneity in terms of their reference, familiarity, and betweenness significances.

Research contributions

This thesis contributes towards better understanding of place in GIScience from place descriptions to landmarks and opening the door for a plethora of future applications towards advances of place-based GIS. Accordingly, this research has focused on place information based on NL descriptions. The major contributions of this research are:
• An implementation of the dynamic sketch map drawing strategy from NL place descriptions of places, without the use of additional knowledge sources.

• A new approach for generating place graphs from large corpora, which provides an efficient way of harvesting place descriptions for a target environment from the Web.

• A novel approach for matching place graphs with spatial semantics, which generates a knowledge graph that is fully scalable in spatial coverage as well as spatial granularity.

• A landmark extraction model based on human spatial knowledge, which provides a wide range of place categories and accommodates different contexts, and thus, provides landmarks for different conversational contexts.

Future works

Although the approaches described in this thesis are efficient and robust for processing place descriptions, there are some limitations of the work, which indicate directions that could be pursued in the future.

Firstly, with the spatial information integration via the similarity matching process, future work includes further studies on how to define the meaning of the measured similarities and how to determine the best threshold value and the individual weights automatically.

Secondly, the combination of gazetteer-based toponym disambiguation methods can be considered since the geographic references coming with a gazetteered entry provide additional evidence for similarity. Another line of future work considers an application domain such as emergency call services, embedding this technique in an emergency GIS. In this way, the textual descriptions of callers can be put to better use.

Thirdly, landmarks extracted from place descriptions in different conversational contexts differ largely, justifying from hindsight an approach that collects context-specific landmarks. With regards to its capability, the LEM has demonstrated a flexibility not known from other landmark identification methods suggested so far. However, it is left for future work to make proper use of these contextualized landmarks.

Lastly, a critical investigation of the quality of the identified landmarks, such as their success to convey certain spatial information, or their density, has to be determined in the future. Another line of future work considers geo-referencing of the extracted landmarks, in order to locate them on the maps of GISs.

To sum up, this research has achieved an automation of the developed approaches for place descriptions, and has demonstrated the
novel methods to facilitate the automatic collection and classification of place descriptions, the automatic integration of spatial information, and the automatic landmark extraction. Future developments will show to what extent the presented approaches are applicable in many applications or situations.


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