# HYBRID FUZZY MULTI-OBJECTIVE PARTICLE SWARM OPTIMIZATION FOR TAXONOMY EXTRACTION

MOHAMMAD SYAFRULLAH

UNIVERSITI TEKNOLOGI MALAYSIA

# HYBRID FUZZY MULTI-OBJECTIVE PARTICLE SWARM OPTIMIZATION FOR TAXONOMY EXTRACTION

MOHAMMAD SYAFRULLAH

A thesis submitted in fulfilment of the
requirements for the award of the degree of
Doctor of Philosophy (Computer Science)

Faculty of Computing
Universiti Teknologi Malaysia

SEPTEMBER 2015

To my beloved family.

## ACKNOWLEDGEMENT

All praise and glory is to almighty Allah Subhanahu wa ta'ala who gave me the courage and patience to carry out this work. Peace and blessings of Allah be upon his last prophet Muhammad shalallahu alaihi wassalam, his family and companions.

I would like to express my deep gratitude to my supervisor Professor Dr. Naomie Salim for her unconditional help, guidance, encouragement, support and valuable suggestions during the preparation of my thesis.

I want to especially thank my parents, family members, especially my mother, my wife and my children for their love, continuous support and encouragement. Also, I want to thank all my friends and my lab mates for their support and helps.

## ABSTRACT

Ontology learning refers to an automatic extraction of ontology to produce the ontology learning layer cake which consists of five kinds of output: terms, concepts, taxonomy relations, non-taxonomy relations and axioms. Term extraction is a prerequisite for all aspects of ontology learning. It is the automatic mining of complete terms from the input document. Another important part of ontology is taxonomy, or the hierarchy of concepts. It presents a tree view of the ontology and shows the inheritance between subconcepts and superconcepts. In this research, two methods were proposed for improving the performance of the extraction result. The first method uses particle swarm optimization in order to optimize the weights of features. The advantage of particle swarm optimization is that it can calculate and adjust the weight of each feature according to the appropriate value, and here it is used to improve the performance of term and taxonomy extraction. The second method uses a hybrid technique that uses multi-objective particle swarm optimization and fuzzy systems that ensures that the membership functions and fuzzy system rule sets are optimized. The advantage of using a fuzzy system is that the imprecise and uncertain values of feature weights can be tolerated during the extraction process. This method is used to improve the performance of taxonomy extraction. In the term extraction experiment, five extracted features were used for each term from the document. These features were represented by feature vectors consisting of domain relevance, domain consensus, term cohesion, first occurrence and length of noun phrase. For taxonomy extraction, matching Hearst lexico-syntactic patterns in documents and the web, and hypernym information form WordNet were used as the features that represent each pair of terms from the texts. These two proposed methods are evaluated using a dataset that contains documents about tourism. For term extraction, the proposed method is compared with benchmark algorithms such as Term Frequency Inverse Document Frequency, Weirdness, Glossary Extraction and Term Extractor, using the precision performance evaluation measurement. For taxonomy extraction, the proposed methods are compared with benchmark methods of Feature-based and weighting by Support Vector Machine using the f-measure, precision and recall performance evaluation measurements. For the first method, the experiment results concluded that implementing particle swarm optimization in order to optimize the feature weights in terms and taxonomy extraction leads to improved accuracy of extraction result compared to the benchmark algorithms. For the second method, the results concluded that the hybrid technique that uses multi-objective particle swarm optimization and fuzzy systems leads to improved performance of taxonomy extraction results when compared to the benchmark methods, while adjusting the fuzzy membership function and keeping the number of fuzzy rules to a minimum number with a high degree of accuracy.

# ABSTRAK

Pembelajaran Ontologi merujuk kepada sokongan automatik pembangunan ontologi untuk menghasilkan lapisan ontologi yang terdiri daripada lima jenis output termasuk: istilah, konsep, hubungan taksonomi, hubungan bukan taksonomi dan aksiom. Pengekstrakan istilah merupakan prasyarat untuk semua aspek pembelajaran ontologi. Ia merupakan perlombongan automatik istilah lengkap daripada dokumen input. Satu lagi bahagian penting dalam ontologi ialah taksonomi, atau hierarki konsep. Ia mempamerkan ontologi dalam bentuk pohon dan menunjukkan warisan antara sub konsep dan super konsep. Dalam kajian ini, dua kaedah telah dicadangkan untuk meningkatkan prestasi keputusan pengekstrakan. Kaedah pertama menggunakan pengoptimuman kerumunan partikel untuk mengoptimumkan pemberat cirinya. Kelebihan pengoptimuman kerumunan partikel ialah ia boleh mengira dan melaraskan pemberat setiap ciri mengikut nilai yang sesuai, dan ia digunakan untuk meningkatkan prestasi pengekstrakan istilah dan taksonomi. Kaedah kedua menggunakan teknik hibrid yang menggunakan pengoptimuman kerumunan partikel pelbagai objektif dan sistem kabur yang memastikan fungsi keahlian dan peraturan sistem kabur adalah optimum. Kelebihan menggunakan sistem kabur ialah nilai tidak tepat dan nilai tidak menentu pemberat ciri boleh diterima semasa proses pengekstrakan. Kaedah ini digunakan untuk meningkatkan prestasi pengekstrakan taksonomi. Dalam uji kaji pengekstrakan istilah, lima ciri-ciri yang diekstrak digunakan untuk setiap istilah daripada dokumen. Ciri-ciri ini diwakili oleh vektor ciri yang terdiri daripada perkaitan domain, persetujuan domain, kepaduan istilah, kejadian pertama dan panjang frasa kata nama. Untuk pengekstrakan taksonomi, pemadanan corak leksiko-sintaksis Hearst dalam dokumen dan web, dan maklumat hipernim WordNet digunakan sebagai ciri-ciri yang mewakili setiap pasangan istilah daripada teks. Kedua-dua kaedah dinilai menggunakan set data yang mengandungi dokumen berkenaan pelancongan. Untuk pengekstrakan istilah, kaedah yang dicadangkan itu dibandingkan dengan algoritma penanda aras Frekuensi Istilah dan Frekuensi Dokumen Songsang, Keanehan, Pengekstrakan Glosari dan Pengekstrakan Istilah, menggunakan pengukuran penilaian kepersisan. Untuk pengekstrakan taksonomi, kaedah yang dicadangkan dibandingkan dengan kaedah berdasarkan ciri dan mesin sokongan vektor menggunakan ukuran-f, ukuran kepersisan dan ukuran perolehan kembali. Untuk kaedah pertama, keputusan uji kaji menyimpulkan bahawa melaksanakan pengoptimuman kerumunan partikel untuk mengoptimumkan pemberat ciri dalam pengekstrakan istilah dan taksonomi menghasilkan ketepatan yang lebih baik bagi keputusan pengekstrakan berbanding dengan algoritma penanda aras. Bagi kaedah kedua, keputusan juga menyimpulkan bahawa teknik hibrid yang menggunakan pengoptimuman kerumunan partikel pelbagai objektif dan sistem kabur menghasilkan prestasi yang lebih baik bagi keputusan pengekstrakan taksonomi berbanding kaedah penanda aras, di samping menyesuaikan fungsi keahlian kabur dan menyimpan jumlah peraturan kabur yang minimum dengan tahap ketepatan yang tinggi.

# TABLE OF CONTENTS

# LIST OF ALGORITHMS

# LIST OF TABLES

## LIST OF FIGURES

# LIST OF APPENDICES

# CHAPTER 1

# INTRODUCTION

## 1.1. Introduction

The web is a source of human-computer interaction and appears to be human-readable only. Many individuals realize its benefits in his/her routine life. Although its structure is recognized by the computer; the semantic and content related aspects are not understood by the computer. In addition, major IT applications are implemented by building a specific mapping between data source and data model. Problems can be appear in the application development as a result of data integration. However, semi-automatic mapping could be performed if the data sources contain semantic descriptors that are machine-readable.

This issue can be addressed by the semantic web. Berners-Lee (1999) has described that the advanced level of the existing web is known as the semantic web with clear and precise meanings to the information, enables the integrated work environment for humans and machines, and also makes the knowledge acquisition process becomes easier. Representation of the data in structured form is one of the foundations of the semantic web vision for understanding of complicated matters with their complete solutions. Rather than information retrieval, the knowledge acquisition is being emphasized by the semantic web in which there is a linguistic sort of comparison between search results and the applied keywords. Upon the request of a user, the computer will also be able to understand the problem, and accordingly suggest the solution within the semantic web domain. In order to bridge the semantic gap, the semantic web depends on ontology so that the support for knowledge acquisition may be delivered effectively.

A categorical arrangement of a shared conceptualization regarding the area of interest is believed to be as the “ontology” (Gruber, 1993). It is a data model through which the objects in a specific domain are analysed along with identifying the relations among them. As far as the information systems are concerned, ontology should be confined to a given domain of interest and should be carried out automatically, so that the knowledge could be represented and exchanged to the community or group (Buitelaar *et al.*, 2005). Ontology can behave as an interface or medium, so that a common understanding and knowledge among machines and humans could be delivered, since it is machine understandable. The terms, concepts, relations, and rules, in addition to the axioms, are among the components of ontology procedures.

On the other hand, it is a difficult task to accomplish the semantic web. Since the developers use the bottom-up approach to build the semantic web, therefore integration of ontology or knowledge structures is a hard process. Consequently, in the semantic web development, ontology engineering is believed to be as a critical process, because the practical implementation of the web contains huge and substantial magnitude of knowledge. Ontology maintenance and ontology acquisition are the two tasks in which ontology engineering can be broadly categorized. The maintenance of the current ontology and the creation of new concepts are performed by these tasks.

The complexity in knowledge capturing, also known as the *knowledge acquisition bottleneck*, has slowed down the evolvement towards semantic web. According to the researchers, the conventional method of ontology engineering is basically a procedure, which is expensive, challenging and time-consuming (Cimiano, 2006; Malo *et al.*, 2010; Nazri, 2011; Sun *et al.*, 2012). The ontology is believed to have a large domain analysis. The major trouble in this overall process is promoting the contraction of the model by simultaneously evaluating constant and significant generalizations. Ontology engineering actually becomes a stimulating initiative because of the exchange between modelling an enormous amount of knowledge and delivering as many constructs as possible so that the model can be kept abridged. In addition, ontology construction is a challenging activity because of the fact that different parties have to agree on particular design choices, since they are usually shared by a community or group of people (Cimiano, 2006).

For ontology construction, the provision of an automatic or semi-automatic tool is a solution to this issue. The ontology learning is a process of (semi-)automatic construction, enrichment and adaptation of ontologies. Several ontology learning techniques have been differentiated and the input type used for learning has been emphasized by Maedche and Staab (2001). The following classification has been suggested by them for this purpose: ontology learning from textual resources (texts), from knowledge base, from dictionaries, from relational schemata and from semi-structured schemata.

Through natural language analysis methods, the mining of ontologies to texts are included in ontology learning techniques from the textual procedures. The most renowned methodologies on the basis of this research study are association rules (Agrawal *et al.*, 1993; Kim and Storey, 2012; Nebot and Berlanga, 2012; Ferraz and Garcia, 2013; Galárraga *et al.*, 2013), pattern-based extraction (Hearst, 1992; Cimiano *et al.*, 2004; Buitelaar *et al.*, 2005; Jiang and Tan, 2010; Kozareva and Hovy, 2010; Weichselbraun *et al.*, 2010; Sánchez *et al.*, 2010; Hourali and Montazer, 2011; Fader *et al.*, 2011; Navigli *et al.*, 2011; IJntema *et al.*, 2012; Sánchez *et al.*, 2012), ontology pruning (Kietz *et al.*, 2000; Jiang and Tan, 2010; Gaeta *et al.*, 2011; Lee and Kim, 2011; Navigli *et al.*, 2011; Zavitsanos *et al.*, 2011; Ahmed *et al.*, 2012; Benites and Sapozhnikova, 2012; Zhao and Ichise, 2012; Manda *et al.*, 2013; Serra *et al.*, 2014), conceptual clustering (Faure *et al.*, 2000; Vitanyi *et al.*, 2009; Hourali and Montazer, 2011; Gharib *et al.*, 2012; Punuru and Chen, 2012; Spanakis *et al.*, 2012; Zong *et al.*, 2012; Knijff *et al.*, 2013), concept learning (Hahn *et al.*, 2000; Jiang and Tan, 2010; Lehmann and Hitzler, 2010; Santoso *et al.*, 2011; Ruiz-Martínez *et al.*, 2011; Lehmann *et al.*, 2011) and soft computing (Nazri *et al.*, 2009; Nazri *et al.*, 2010; Nazri *et al.*, 2011; Chen *et al.*, 2011; Paukkeri *et al.*, 2012; Kaufmann *et al.*, 2013). Yet the aim of fully automating the ontology development has not been acquired by this research field although there is a good progress in the recent years. However, the key challenge would be fully automated ontology learning.

## 1.2. Background of Problem

Discovery of terms, concepts, relations and axioms from textual data and applying them to build and sustain ontology is the process of ontology learning from text (Wong *et al.*, 2012). In the construction of ontology learning systems, procedures from established fields, for example, information retrieval, natural language processing and data mining have maintained great significance.

Over the last decade, the progress in ontology learning has been uplifted through several recognized techniques from established fields, for instance machine learning, information retrieval, natural language processing, and data mining in addition to knowledge representation and reasoning. For analysing links between concepts among texts using matrices, vectors (Fortuna *et al.*, 2005; Fortuna, 2011; Wei *et al.*, 2012) and probabilistic theorems (Yang and Calmet, 2005; Wang *et al.*, 2010; Drumond and Girardi, 2010; Abeyruwan *et al.*, 2013), numerous algorithms have been delivered by information retrieval (Wong *et al.*, 2012).

However, because of the substantial datasets in a supervised or unsupervised manner based on the extensive statistical analysis, the skill for extracting patterns and rules has to be provided by data mining and machine learning. In order to reveal concept relations and representations through linguistic cues, the tools for evaluating natural language text across several language levels (e.g., syntax, morphology and semantics) are provided by natural language processing. As a result of knowledge reasoning and representation, the new knowledge can be inferred by specifying and representing the ontological components in a desirable way. Depending upon the execution of tasks, there can be a variation among the techniques exercised by different systems. The linguistics-based, statistics-based, or hybrid (combination of these methods) can be the normal classification of the techniques (Wong *et al.*, 2012).

Ontology learning, sometimes called the ontology learning layer cake (Buitelaar *et al.*, 2005), consists of five kinds of output that include terms, concepts, taxonomy relations, non-taxonomy relations and axioms. Particular tasks have to be completed in order to get these outputs and these set of tasks are unique to each output.

Term extraction is a prerequisite for all aspects of ontology learning. In the ontology development process, the term extraction is actually one of the layers, whose responsibility is to automatically mine the complete terms present in the input document. To produce a list of important and relevant terms associated with the input document is the key aim of this process. Primarily, for the textual corpora processing, the literature has considerably witnessed several techniques. Majority of these are based on the NLP method and terminology, linguistic techniques, clustering techniques and information/statistical retrieval methods (Cimiano, 2006).

Regarding other words in a corpus based on word occurrence frequencies, the significance of each word is normally calculated by the statistical methods. Various works have been applied in statistical methods for term extraction. Most of them are based on an information retrieval method for term indexing (Salton and Buckley, 1988; Medelyan and Witten, 2005; Turney and Pantel, 2010; Pinnis *et al.*, 2012). Other methods use the notion of "weirdness" (Ahmad *et al.*, 1999; Lucanský *et al.*, 2011; Clouet *et al.*, 2012; Loukachevitch and Nokel, 2013), latent semantic indexing (Fortuna *et al.*, 2005; Zavitsanos *et al.*, 2010), and domain pertinence (Navigli and Velardi, 2004; Sclano and Velardi, 2007; Ittoo and Bouma, 2013).

In statistical approaches, the term extraction system finds out the importance of every word with regard to other words in a quantity as per word occurrence frequencies. There are different features of every technique and it leads to a list of the terms through calculation of the scores of the features for every term. The total scores of the features are combined together to result in the scores of the term. Eventually, a set of the highest scoring terms will be obtained. The precision of the extraction is extremely reliant on the calculation of the term scores in accordance with its features. For instance, two features were used by Park *et al.* (2002) and Kozakov *et al.* (2004). These are domain specificity and term cohesion for the purpose of term weight calculation. The basic concept of domain specificity is that: if a term is used more often in a domain-specific document than in other document collections, it is likely to be a domain-specific term. In their paper, they evaluate the domain-specificity of a multi-word term based on the relative probability of the occurrence of all the words in the term in the given domain-specific text and in a general corpus. Term cohesion is a measurement used to compute the cohesion of multi-word terms and is proportional to the co-occurrence frequency and the length of the term.

A method known as TermExtractor was formulated by Sclano and Velardi (2007) in order to determine the pertinent terms in two steps. They make use of three features so as to calculate term weight. These are domain pertinence, domain consensus and lexical cohesion. The feature based on coefficients is combined in this study, where the coefficients are in accordance with user-adjustable. The basic concept of domain pertinence is to compare the number of times a term appears in a particular domain with the number of times it appears in other domains. The domain pertinence is high if a term appears frequently in the domain of interest and infrequently in the other domains used for contrast. Park *et al.* (2002) use a similar method for filtering, called domain specificity. Domain consensus focuses on the distribution of a term across the documents within the domain. If domain consensus is high it presents an even probability distribution across the documents chosen to represent the domain. This novel measure was introduced by Navigli and Velardi (2002). Lexical cohesion is a measurement used to evaluate the degree of cohesion among words that compose a terminological string t. This measure was first introduced by Park *et al.* (2002) and proved to be more effective than other measures of cohesion within literature. It identifies cohesion as high if the words composing the term are more frequently found within the term than alone in texts. In their study, they combine the feature based on the coefficients, where the coefficients are based on user-adjustable.

With respect to this issue, this research aims to investigate the features that are effective to create an accurate term extraction through optimization and adjustment of feature weights. PSO will be used in this study for optimization of the corresponding weights of every feature and consequently attain a suitable set of feature weights. The advantage of particle swarm optimisation, which can calculate and adjust the weight of each feature, should ensure that the weight of each feature is adjusted according to the appropriate value. Thus, the method recommended through this study is one that utilises the advantage of particle swarm optimization in order to obtain important and relevant terms from the document.

An important part of ontology is its taxonomy, or the hierarchy of concepts. It presents a tree view of the ontology and shows inheritance between sub concepts and super concepts. Various methods have been presented in the literature reviews which have effectively enhanced the taxonomy extraction process. There are three distinct learning methods that could be employed. First of all, certain methods depend on document-based concept of term submission (concept formation) (Sanderson, 1999; Knijff, *et al.*, 2011; Medelyan *et al.*, 2013). Secondly, certain researchers state that terms or words are semantically similar to such a level that they even share similar syntactic contexts (synonym extraction) (Caraballo and Charniak, 1999; Bisson *et al.*, 2000; Bhatt and Bhattacharyya, 2012). Lastly, some researchers have tried to determine taxonomic relations presented in texts by matching several patterns related to the language in which the documents are provided (Berland and Charniak, 1999; Navigli *et al.*, 2011; Li *et al.*, 2012; Taba and Caseli, 2012; Velardi *et al.*, 2013).

Pattern-based techniques are heuristic methods which use regular expressions that have been effectively implemented for information extraction. In this method, texts are scanned for specific lexical-syntactic patterns which show a relation of interest (Hearst, 1992; Cimiano, 2004; Jiang and Tan, 2010; Kozareva and Hovy, 2010; Sánchez *et al.*, 2010; Hourali and Montazer, 2011; Fader *et al.*, 2011; Navigli *et al.*, 2011; IJntema *et al.*, 2012; Sánchez *et al.*, 2012). A novel approach for learning taxonomic relations between terms based on Hearst pattern has been presented by Cimiano *et al.* (2004). This technique involves the use of multiple and heterogeneous sources of evidence. They use a machine-learning technique in which standard classifiers are used so that an optimal combination of the features is obtained. Standard regression SVM is used in the paper. There is a problem by using Support Vector Machine (SVM) classifier, as seen in their study. The weight of feature generated by the SVM can be negative values. This is because SVM always tries to find the highest accuracy regardless of the weight of each feature.

With respect to this matter, this research aims to investigate the features that would be successful in developing an accurate taxonomy extraction through adjustment and optimization of the feature weights. PSO will be used in this research so that corresponding weights of every feature is optimized and a suitable set of feature weights is attained.

The aim of this research is also to combine all the taxonomy features without weighting all the features. However, this could result in imprecise and uncertain taxonomy scores. To solve this issue, fuzzy systems are used. A hybrid approach is demonstrated which will enhance the taxonomy extraction process. This hybrid approach involves a combination of Continuous Particle Swarm Optimisation (PSO) and Discrete Binary PSO (BPSO) for the optimisation of fuzzy systems. Thus, PSO and BPSO are utilised in this approach so that the membership functions and rule sets of fuzzy systems are respectively optimised. An advantage of fuzzy systems is that they enable toleration of imprecise and uncertain values of feature weights when the taxonomy extraction process is being carried out. The advantage of particle swarm optimisation which is used to solve optimisation issues is that it enhances the performance of fuzzy systems through adjustment of the rule set and the membership function. Thus, this study recommends the use of a method that utilises the advantages of particle swarm optimisation and fuzzy system so that important and relevant taxonomies from the document are extracted.

## 1.3. Problem Statement

In the literature, many different approaches, techniques and algorithms have been used for term extraction and taxonomy extraction. Many researchers have attempted to design methods and approaches that increase the accuracy of the term extraction and taxonomy extraction. This research aims to propose methods to extract terms and taxonomies that are important and relevant to a particular domain.

The first part of this research will investigate what features are effective in creating an accurate term extraction and taxonomy extraction by optimizing and adjust the feature weights. PSO will be applied in this research, as earlier studies have suggested that the PSO method was generally found to perform better than other evolutionary-based optimization algorithms in terms of success rate and solution quality, according to Hassan *et al.* (2004), Elbeltagi *et al.* (2005) and Yang (2008). PSO is frequently observed as function optimization, while the range of the problem to which PSO has been applied is quite broad. In the first method, PSO will be utilized to optimize the corresponding weights of each feature in order to obtain an appropriate set of feature weights.

The second part of this research will combine the taxonomy features without weighting them. This could make the taxonomy scores imprecise and uncertain. Fuzziness is a way to represent uncertainty, possibility and approximation. If something is fuzzy, this means it is not possible to define its exact values precisely. Fuzzy logic is a good tool for situations where uncertainty is somewhat intrinsic to the system. Therefore, this research will use fuzziness to represent uncertainty, as the literature has identified fuzzy systems as being advantageous because they are tolerant of imprecise and uncertain data.

Improving the performance of fuzzy systems is also an important issue. In the literature review, several techniques have been developed which successfully improve the performance in fuzzy system. Adjusting the membership function and finding the optimal number of rules can achieve a satisfactory level of performance in the fuzzy system. For example, Esmin and Lambert-Torres (2006, 2007, and 2010) and Lambert-Torres *et al.* (2000) have shown an efficient PSO based approach to constructing and optimizing a fuzzy rule base and fuzzy membership function. Research by Kiani and Akbarzadeh (2006) proposed a technique for combining a Genetic Algorithm (GA) and Genetic Programming (GP) to optimize the rule sets and membership functions of fuzzy systems. Subsequently, in the second method, PSO and BPSO will be used to optimize the membership functions and rule sets of fuzzy systems, respectively.

Considering the background of the problem and the proposed method, the research questions for the research activities are as follows:

1. What are the key features that can be used to extract term and taxonomy according to a particular domain?
2. How can particle swarm optimization be implemented in term extraction and taxonomy extraction?
3. How can the hybrid method of fuzzy and multi-objective particle swarm optimization be implemented in taxonomy extraction?

## 1.4. Objectives of Study

This research aims to propose methods for extracting terms and taxonomies that are important and relevant to a particular domain. The primary focus of this research is to propose methods for extracting terms and taxonomies from textual resources (text) using particle swarm optimization and fuzzy systems. A hybrid method using multi-objective particle swarm optimization and fuzzy systems for taxonomy extraction will also be explored. In the first method PSO will be employed to optimize the corresponding weights of each feature and obtain an appropriate set of feature weights. In the second method PSO and BPSO will be used to optimize the membership functions and rule sets of fuzzy systems, respectively.

In order to achieve the aim of the study, the following are objectives of this research:

1. To identify important features that can be used to extract terms and taxonomies relating to a particular domain.
2. To propose new term extraction and taxonomy extraction methods based on the particle swarm algorithm.
3. To propose new taxonomy extraction methods based on hybrid fuzzy and multi-objective particle swarm optimization.

## 1.5. Scope of Study

This research will involve an in-depth study of term extraction using particle swarm optimization and taxonomy extraction using hybrid multi-objective particle swarm optimization and fuzzy systems. This research will focus primarily on term extraction and taxonomy extraction from textual resources (texts). In order to achieve the research objectives, the scope of this study is as follows:

1. To focus on term extraction using particle swarm optimization and taxonomy extraction using multi-objective particle swarm optimization and fuzzy systems, and to identify possible improvements using the hybrid method.

2. PSO will be utilized to optimize the corresponding weights of each feature and obtain an appropriate set of feature weights.
3. PSO and BPSO will be used to optimize the membership functions and rule sets of fuzzy systems.
4. One part of the experiment will be developed in PHP in order to obtain search results via Google. Other parts of the experiment will be coded using Java, Visual Basic, and Python.
5. jFuzzyLogic is an open source fuzzy system that will be used to implement the optimization of the membership functions and rule sets of fuzzy systems using PSO and BPSO.
6. WordNet version 2.1 will be used for finding the hypernym of the term.
7. Experiments and evaluations using the proposed methods will be conducted by using the data about tourism that has already been used by Cimiano[1]. The data is approximately a million tokens in size and includes descriptions of countries, cities, places, regions, sights etc. from all continents. For this experiment 1500 documents will be used as datasets.
8. Reuters-21578 will be used in the experiment as contrastive documents.
9. The evaluation and comparison of the proposed methods will be based on standard performance metrics such as precision, recall and f-measure.

## 1.6. Significance of Study

This research will investigate term extraction and taxonomy extraction by using a statistical method and a soft computing method, which both help to improve the performance of extracting term and taxonomy. The significance of this research is to propose methods for taxonomy extraction by using hybrid methods.

The first method to be used will be particle swarm optimization in order to optimize the weights of the features. The advantage of particle swarm optimization is that it can calculate and adjust the weight of each feature, and should ensure that the weight of each feature is adjusted to the appropriate value. Subsequently, this study

[1] http://olc.ijs.si/lpTxt/

use particle swarm optimization to extract the important and relevant terms and taxonomies from the document.

The second method will include the use of PSO and BPSO in order to optimize the membership functions and rule sets of fuzzy systems. The advantage of using a fuzzy system is that the imprecise and uncertain values of feature weights can be tolerated during the taxonomy extraction process. Conversely, particle swarm optimization is advantageous because it can solve the problem of optimization and can be used to improve the performance of fuzzy systems by adjusting the membership function and the rule set. Consequently, this study has proposed a method that will draw on the advantages of both fuzzy systems and particle swarm optimization to extract the important and relevant taxonomies from the document.

## 1.7. Structure of the Thesis

This thesis will be organized into seven chapters, as outlined below:

Chapter 2: Literature Review

This chapter will present background information relating to ontologies and related terms. Following this, the state-of-the-art approaches in ontology learning from text will be presented. This chapter will contain an overview surveying the current information available in this research area, including existing techniques, methods and approaches. Some further information and issues relating to term extraction and taxonomy extraction, particle swarm optimization, fuzzy systems will also be reviewed, as they are significant to this research.

Chapter 3: Research Methodology

This chapter will describe the methodology used to achieve the objectives of this research. It will also explain the main experiments that will be conducted as part of this research, including the features of fuzzy system and particle swarm based term extraction and taxonomy extraction. This chapter will also discuss the dataset and evaluation measurement of the proposed method.

Chapter 4: Improving Term Extraction Using Particle Swarm Optimization

This chapter will describe the use of the PSO algorithm to improve the performance of term extraction. This optimization technique will be used to find the optimal weight of each feature to produce the best term score with the aim of deciding whether the terms are important and relevant to a particular domain or not. This chapter will include the results of the experiment, performance analysis, as well as discussion of the experiment and a conclusion.

Chapter 5: Using Particle Swarm Optimization to Improve the Precision and Recall of Taxonomy Extraction

This chapter will describe the use of the PSO algorithm for automatic acquisition of concept hierarchy from text documents. In this proposed method, PSO will be used to adjust the weights of each feature. This optimization technique will be used to find the optimal weight of each feature to produce the best taxonomy score. This chapter will include the results of the experiment, performance analysis, further discussion of the experiment and a conclusion.

Chapter 6: Taxonomy Extraction Using Hybrid Fuzzy Multi-Objective Particle Swarm Optimization

This chapter will present the hybrid models based on fuzzy systems and multi-objective particle swarm optimization for automatic acquisition of concept hierarchy from text documents. In this research, a hybrid method that combines the Continuous Particle Swarm Optimization (PSO) and Discrete Binary PSO (BPSO) will also be used to optimize the fuzzy system. The experimental results of the proposed method will also be evaluated by using evaluation measurement, which is precision, recall and f-measure.

Chapter 7: Conclusion

This chapter will highlight the findings and contributions of the research work and present suggestions and further studies.

swarm optimisation and fuzzy system to enhance the quality of the extraction results. Further investigation is required to establish whether these methods could be applied to the other layers. In conclusion, it is recommended that the effectiveness of these methods, when applied to the other layers, should be investigated.

## REFERENCES

Abeyruwan, S., Visser, U., Lemmon, V., and Schürer, S. (2013), "PrOntoLearn: Unsupervised Lexico-Semantic Ontology Generation Using Probabilistic Methods", In Uncertainty Reasoning for the Semantic Web II, pp. 217-236, Springer Berlin Heidelberg, 2013.

Agirre, E., Ansa, O., Hovy, E., and Martinez, D. (2000), "Enriching very large ontologies using the WWW", *Proceedings of The First Workshop on Ontology Learning*, pp. 1-6, Berlin, 25 August 2000.

Agirre, E., Soroa, A., and Stevenson, M. (2010), "Graph-based Word Sense Disambiguation of biomedical documents", *Bioinformatics,* 26(22): 2889-2896, 2010.

Agrawal, R., Imielinski, T., and Swami, A. (1993), "Mining association rules between sets of items in large databases", *Proceedings of the ACM SIGMOD International Conference on Management of Data*, pp. 207-216, 1993.

Agrawal, R., and Srikant, R. (1994), "Fast Algorithms for mining association rules", *Proceedings of the 20th International Conference on Very Large Databases (VLDB)*, pp. 487-499, 1994.

Ahmad, K., Gillam, L., and Tostevin, L. (1999), "University of Surrey participation in TREC 8: Weirdness Indexing for Logical Document Extrapolation and Retrieval (WILDER)", *Proceedings of The Eighth Text Retrieval Conference (TREC-8)*, pp. 717-724, Gaithersburg, Maryland, 16-19 November 1999.

Ahmed, K. B. S., Toumouh, A., and Malki, M. (2012), "Effective Ontology Learning: Concepts' Hierarchy Building using Plain Text Wikipedia", *Proceedings of CEUR Workshop*, pp. 170-178, 2012.

Al Moubayed, N. (2014), "Multi-Objective Particle Swarm Optimisation: Methods and Applications", Doctor Philosophy, Robert Gordon University, Aberdeen

Alani, H., Kim, S., Millard, D. E., Weal, M. J., Hall, W., Lewis, P. H., and Shadbolt, N. R. (2003), "Automatic Ontology-Based Knowledge Extraction from Web Documents", *IEEE Intelligent Systems*, 18 (1): 14-21, 2003.

Alcalá, R., Gacto, M. J., Herrera, F., and Alcalá-Fdez, J. (2007), "A Multi-Objective Genetic Algorithm for Tuning and Rule Selection to Obtain Accurate and Compact Linguistic Fuzzy Rule-Based Systems", *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, 15(5): 539-557, 2007.

Alcalá, R., Nojima, Y., Herrera, F., and Ishibuchi, H. (2011), "Multiobjective genetic fuzzy rule selection of single granularity-based fuzzy classification rules and its interaction with the lateral tuning of membership functions", *Soft Computing*, 15(12): 2303-2318, 2011.

Aleksandrov, M., and Strapparava, C. (2012), "NgramQuery - Smart Information Extraction from Google N-gram using External Resources", *Proceedings of the Eight International Conference on Language Resources and Evaluation*, pp. 563-568, Istanbul, 23-25 May 2012.

Alfonseca, E., and Manandhar, S. (2002a), "An unsupervised method for general named entity recognition and automated concept discovery", *Proceedings of the 1st International Conference on General WordNet*, pp. 1-9, 2002.

Alfonseca, E., and Manandhar, S. (2002b), "Extending a Lexical Ontology by a Combination of Distributional Semantics Signatures", *Proceedings of the 13th International Conference on Knowledge Engineering and Knowledge Management (EKAW)*, pp. 1-7, Spain, 1-4 October 2002.

Angeline, P. J. (1998), "Using selection to improve particle swarm optimization", *Proceedings of The 1998 IEEE International Conference on Evolutionary Computation*, pp. 84–89, Anchorage, 4-9 May 1998.

Artese, M. T., and Gagliardi, I. (2014), "Multilingual Specialist Glossaries in a Framework for Intangible Cultural Heritage", In Digital Heritage. Progress in Cultural Heritage: Documentation, Preservation, and Protection, pp. 767-776, Springer International Publishing, 2014.

Auger, A., and Barrière, C. (2008), "Pattern-based approaches to semantic relation extraction: A state-of-the-art", *International Journal of Theoretical and Applied Issues in Specialized Communication*, 14(1): 1–19, 2008.

Aussenac-Gilles, N., Biébow, B., and Szulman, S. (2000a), "Corpus Analysis For Conceptual Modelling", *Proceedings of the 12th International Conference on Knowledge Engineering and Knowledge Management (EKAW)*, pp. 1-8, 2000.

Aussenac-Gilles, N., Biébow, B., and Szulman, S. (2000b), "Revisiting Ontology Design: A Methodology Based on Corpus Analysis", *Proceedings of the 12th International Conference on Knowledge Engineering and Knowledge Management (EKAW)*, pp. 172–188, Juan-les-Pins, France, 2-6 October 2000.

Aussenac-Gilles, N. (2005), "Supervised text analysis for ontology and terminology engineering", *Machine Learning for the Semantic Web*, pp. 1-7, Schloss Dagstuhl, Waden, Germany, 2005.

Aussenac-Gilles, N., and Jacques, M. (2008), "Designing and evaluating patterns for relation acquisition from texts with Cameleon", *Terminology*, 14(1): 45-73, 2008.

Bachimont, B., Isaac, A., and Troncy, R. (2002), "Semantic Commitment for Designing Ontologies: A Proposal", *Proceedings of 13th International Conference on Knowledge Engineering and Knowledge Management*, pp. 114-121, Sigüenza, Spain, 1-4 October 2002.

Barforoush, A. A., and Rahnama, A. (2012), "Ontology Leaning: Revisited ", *Journal of Web Engineering*, 11(4): 269-289, 2012.

Barker, K., and Cornacchia, N. (2000), "Using noun phrase heads to extract document keyphrases", *Proceedings of the 13th Biennial Conference of the Canadian Society on Computational Studies of Intelligence: Advances in Artificial Intelligence*, pp. 40-52, Montreal, Quebec, 14-17 May 2000.

Baroni, M., and Bisi, S. (2004), "Using cooccurrence statistics & the web to discover synonyms in a technical language", *Proceedings of the 4th International Conference of Language Resources and Evaluation (LREC)*, (5): 1725-1728, 2004.

Basili, R., Moschitti, A., Pazienza, M. T., and Zanzotto, F. M. (2001), "A contrastive approach to term extraction", *Proceedings of the 4th Terminology and Artificial Intelligence Conference (TIA)*, Nancy, 3-4 May 2001.

Benites, F., and Sapozhnikova, E. (2012), "Learning different concept hierarchies and the relations between them from classified data", In Intelligent Data Analysis for Real-Life Applications: Theory and Practice, pp. 18-34, IGI Global, 2012.

Berland, M., and Charniak, E. (1999), “Finding parts in very large corpora”, *Proceedings of the 37th annual meeting of the Association for Computational Linguistics on Computational Linguistics*, pp. 57-64, 1999.

Berners-Lee, T., and Fischetti, M. (1999), “Weaving the Web: The Original Design and Ultimate Destiny of the World Wide Web by its Inventor”, 1st Edition, HarperCollins Publishers (1999)

Bhatt, B., and Bhattacharyya, P. (2012), “Domain Specific Ontology Extractor for Indian Languages”, *Proceedings of the 10th Workshop on Asian Language Resources*, pp. 75–84, Mumbai, December 2012.

Biébow, B., and Szulman, S. (1999), “TERMINAE: a linguistic-based tool for the building of a domain ontology”, *Proceedings of the 11th European Workshop on Knowledge Acquisition, Modelling and Management*, pp. 49-66, Dagstuhl, Germany, 1999.

Biemann, C. (2005), “Ontology Learning from Text: A Survey of Methods”, *LDV Forum*, 20(2): 75-93, 2005.

Bird, S., Loper, E., Klein, E., and Baldridge, J. (2008), “Multidisciplinary instruction with the natural language toolkit”, *Proceedings of the 3rd ACL Workshop on Issues in Teaching Computational Linguistics*, pp. 62-70, 2008.

Bisson, G. (1992), “Learning in FOL with a similarity measure”, *Proceedings of the 10th National Conference of Artificial Intelligence*, pp. 82-87, 1992.

Bisson, G., Nédellec, C., and Cañamero, D. (2000), “Designing clustering methods for ontology building – The Mo'K workbench”, *Proceedings of the ECAI Ontology Learning Workshop*, pp. 13-19, Berlin, 25 August 2000.

Bodenreider, O. (2004), “The unified medical language system (UMLS): integrating biomedical terminology”, *Nucleic Acids Research*, 32(Database issue): D267–D270, 2004.

Brewster, C., Iria, J., Zhang, Z., Ciravegna, F., Guthrie, L., and Wilks, Y. (2007), “Dynamic iterative ontology learning”, Proceedings *6th International Conference on Recent Advances in Natural Language Processing*, pp. 1-5, 2007.

Brill, E. (1992), “A simple rule-based part of speech tagger”, *Proceedings of the 3rd Conference on Applied Natural Language Processing*, pp. 152-155, 1992.

Budanitsky, A. (1999), "Lexical semantic relatedness and its application in natural language processing", *Techical Report CSRG-390 Computer Systems Research Group*, University of Toronto, 1999.

Buitelaar, P., and Sacaleanu, B. (2002), "Extending Synsets with Medical Terms", *Proceedings of the First International Conference on Global WordNet*, pp. 21-25, Mysore, India, 2002.

Buitelaar, P., Olejnik, D., and Sintek, M. (2004), "A Protege plug-in for ontology extraction from text based on linguistic analysis", *Proceedings of the 1st European Semantic Web Symposium (ESWS)*, pp. 31-44, Crete, Greece, 10-12 May 2004.

Buitelaar, P., Cimiano, P., and Magnini, B. (2005), "Ontology Learning from Text: An Overview", Ontology Learning from Text: Methods, Evaluation and Applications, IOS Press (2005)

Buscaldi, D., Le Roux, J., Flores, J. J. G., and Popescu, A. (2013), "LIPN-CORE: Semantic Text Similarity using n-grams, WordNet, Syntactic Analysis, ESA and Information Retrieval based Features", *Proceedings of the Second Joint Conference on Lexical and Computational Semantics*, pp. 63-69, Atlanta, June 2013.

Caraballo, S. A., and Charniak, E. (1999), "Determining the specificity of nouns from text", *Proceedings of the 1999 Joint SIGDAT Conference on Empirical Methods in Natural Language Processing and Very Large Corpora*, pp. 63–70, 1999.

Casillas, J., Cordón, O., Del Jesus, M. J., Herrera, F., Casillas, J., and Herrera, F. (2001), "Genetic feature selection in a fuzzy rule based classification system learning process for high-dimensional problems", *Information Sciences*, 136(1-4): 135-157, 2001.

Casillas, J., Cordón, O., Herrera, F., and Magdalena, L. (2003), "Interpretability Improvements to Find the Balance Interpretability-Accuracy in Fuzzy Modeling: An Overview", *In Interpretability Issues in Fuzzy Modeling,* pp. 3-22, Springer Berlin Heidelberg, 2003.

Castillo, J. J. (2010), "A Semantic Oriented Approach to Textual Entailment Using WordNet-Based Measures", In Advances in Artificial Intelligence, pp. 44-55, Springer Berlin Heidelberg, 2010.

Castillo, J. J. (2011), "A WordNet-based semantic approach to textual entailment and cross-lingual textual entailment", *International Journal of Machine Learning and Cybernetics*, 2(3): 177-189, 2011.

Cetisli, B. (2010), "Development of an adaptive neuro-fuzzy classifier using linguistic hedges: Part 1", *Expert Systems with Applications*, 37(8): 6093–6101, 2010.

Chalendar, G., and Grau, B. (2000). "SVETLAN' or How to Classify Words Using Their Context", *In Knowledge Engineering and Knowledge Management Methods, Models and Tools*, Chalendar, G. and Grau, B., (Eds.), Springer Berlin/Heidelberg, pp. 99-112, 2000.

Chandrasekaran, B., Josephson, J. R., and Benjamins, R. (1999), "What Are Ontologies, and Why Do We Need Them?", *IEEE Intelligent Systems and their Applications*, 14(1): 20 – 26, 1999.

Chen, R, Bau, C., and Yeh, C. (2011), "Merging domain ontologies based on the WordNet system and Fuzzy Formal Concept Analysis techniques", *Applied Soft Computing*, 11(2): 1908-1923, 2011.

Church, K. W., and Hanks, P. (1990), "Word association norms, mutual information, and lexicography", *Journal Computational Linguistics*, 16(1): 22-29, 1990.

Ciaramita, M., Gangemi, A., Ratsch, E., Saric, J., and Rojas, I. (2005), "Unsupervised Learning of Semantic Relations between Concepts of a Molecular Biology Ontology", *Proceedings of the 19th International Joint Conference on Artificial Intelligence (IJCAI)*, pp. 659-665, 2005.

Cimiano, P., Hotho, A., and Staab, S. (2004), "Comparing conceptual, divisive and agglomerative clustering for learning taxonomies from text", *Proceedings of the 16th European Conference on Artificial Intelligence (ECAI)*, pp. 435-439, Valencia, Spain, 22-27 August 2004.

Cimiano, P., Pivk, A., Schmidt-Thieme, L., and Staab, S. (2004), "Learning Taxonomic Relations from Heterogeneous Evidence", *ECAI-2004 Workshop on Ontology Learning and Population, A Workshop at the 16th European Conference on Artificial Intelligence*, pp. 1-6, Valencia, Spain, 22-23 August 2004.

Cimiano, P., and Staab, S. (2005), "Learning Concept Hierarchies from text with a Guided Agglomerative Clustering Algorithm", *Proceedings of the ICML 2005 Workshop on Learning and Extending Lexical Ontologies with Machine Learning Methods*, pp. 1-10, Bonn, Germany, 2005.

Cimiano, P., Hotho, A., and Staab, S. (2005), "Learning Concept Hierarchies from Text Corpora using Formal Concept Analysis", *Journal of Artificial Intelligence Research*, 24(1): 305-339, 2005.

Cimiano, P., Pivk, A., Schmidt-Thieme, L., and Staab, S. (2005), "Learning Taxonomic Relations from Heterogeneous Source of Evidence", In Ontology Learning from Text: Methods, Applications and Evaluation, pp. 59-73, IOS Press, 2005.

Cimiano, P. (2006), "Ontology Learning and Population from Text: Algorithms, Evaluation and Applications", 1st Edition, Springer (2006).

Cingolani, P., and Alcalá-Fdez, J. (2012), "jFuzzyLogic: a robust and flexible Fuzzy-Logic inference system language implementation", *Proceedings of IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, pp. 1-8, Brisbane, Australia, 10-15 June 2012.

Cingolani, P., and Alcalá-Fdez, J. (2013), "jFuzzyLogic: a Java Library to Design Fuzzy Logic Controllers According to the Standard for Fuzzy Control Programming", *International Journal of Computational Intelligence Systems*, 6(supp 1): 61-75, 2013.

Clouet, E. L., Gojun, A., Blancafort, H., Guegan, M., Gornostay, T., and Heid, U. (2012), "Reference Lists for the Evaluation of Term Extraction Tools", *Proceedings of Terminology and Knowledge Engineering Conference*, pp. 1-16, Madrid, June 2012.

Coello, C. A. C. (2011), "An Introduction to Multi-Objective Particle Swarm Optimizers", *In Soft Computing in Industrial Applications*, pp. 3-12, Springer Berlin Heidelberg, 2011.

Cunningham, H., Maynard, D., Bontcheva, K., and Tablan, V. (2002), "GATE: An Architecture for Development of Robust HLT Applications", *Proceedings of the 40th Annual Meeting on Association for Computational Linguistics (ACL)*, pp. 168-175, 2002.

Dagan, I., Glickman, O., and Magnini, B. (2005), "The pascal recognizing textual entailment challenge", *Proceedings of the 1st International Conference on Machine Learning Challenges: Evaluating Predictive Uncertainty Visual Object Classification, and Recognizing Textual Entailment*, pp. 177-190, Southampton, UK, 2005.

Deane, P. (2005), "A nonparametric method for extraction of candidate phrasal terms", *Proceedings of the 43rd Annual Meeting on Association for Computational Linguistics*, pp. 605-613, University of Michigan, USA, 2005.

Derbel, I., and Hachani, N. (2008), "Membership Functions Generation Based on Density Function", *Proceedings of International Conference on Computational Intelligence and Security*, pp. 96-101, Suzhou, China, 13-17 December 2008.

Ding, Y., and Foo, S. (2002), "Ontology research and development. Part 1 – a review of ontology generation", *Journal of Information Science*, 28(2): 123-136, 2002.

Drumond, L., and Girardi, R. (2008), "A Survey of Ontology Learning Procedures", *Proceedings of the 3rd Workshop on Ontologies and their Applications*, pp. 1-12, Salvador, Bahia, Brazil, 26 October 2008.

Drumond, L., and Girardi, R. (2010), "Extracting ontology concept hierarchies from text using Markov logic", *Proceedings of the 2010 ACM Symposium on Applied Computing*, pp. 1354-1358, Sierre, 22-26 March 2010.

Dubois, D., and Prade, H. (1996), "What are fuzzy rules and how to use them", *Fuzzy Sets and Systems*, 84(2): 169–185, 1996.

Eberhart, R. C., and Kennedy, J. (1995a), "A new optimizer using particle swarm theory", *Proceeding of The Sixth International Symposium on Micro Machine and Human Science*, pp. 39-43, Nagoya, 4-6 October 1995.

Eberhart, R. C., and Shi, Y. (1998), "Comparison between genetic algorithms and particle swarm optimization", *Proceedings of Annual Conference on Evolutionary Programming*, pp. 611-616, San Diego, California, 25–27 March 1998.

Eberhart, R. C., and Shi, Y. (2001a), "Particle swarm optimization: developments, applications and resources", *Proceedings of the 2001 Congress on Evolutionary Computation*, pp. 81-86, Seoul, 27-30 May 2001.

Eberhart, R. C., and Shi, Y. (2001b), "Tracking and optimizing dynamic systems with particle swarms", *Proceedings of the 2001 Congress on Evolutionary Computation*, pp. 94-100, Seoul, 27-30 May 2001.

Elbeltagi, E., Hegazy, T., and Grierson, D. (2005), "Comparison among five evolutionary-based optimization algorithms", *Advanced Engineering Informatics*, 19(1): 43-53, 2005.

Elragal, H. M. (2011), “Improving Accuracy of Fuzzy Classifiers using Swarm Intelligence”, *Proceedings of 3rd International Conference on Communication Software and Networks*, pp. 170-174, Xi’an, 27-29 May 2011.

Esmin, A. A. A., and Lambert-Torres, G. (2006), “Fitting Fuzzy Membership Functions Using Hybrid Particle Swarm Optimization”, *Proceedings of Systems, Man and Cybernetics*, pp. 2112–2119, Vancouver, 16-21 July 2006.

Esmin, A. A. A., and Lambert-Torres, G. (2007), “Evolutionary computation based fuzzy membership functions optimization”, *Proceedings of Systems, Man and Cybernetics*, pp. 823–828, Montreal, 7-10 October 2007.

Esmin, A. A. A., and Lambert-Torres, G. (2010), “Generate and optimize fuzzy rules using the Particle Swarm Algorithm”, *Proceedings of Systems, Man and Cybernetics*, pp. 4244–4250, Istanbul, 10-13 October 2010.

Etzioni, O., Cafarella, M., Downey, D., Kok, S., Popescu, A., Shaked, T., Soderland, S., Weld, D. S., and Yates, A. (2004), “Web-scale information extraction in KnowItAll (preliminary results)”, *Proceedings of the 13th International Conference on World Wide Web (WWW)*, pp. 100-109, 2004.

Evans, R. (2003), “A framework for named entity recognition in the open domain”, *Proceedings of the International Conference of Recent Advances in Natural Language Processing (RANLP)*, pp. 137-144, 2003.

Faatz, A., and Steinmetz, R. (2002), “Ontology enrichment with texts from the WWW”, *Proceedings of The Second Semantic Web Mining Workshop*, pp. 1-15, Helsinki, 20 August 2002.

Fader, A., Soderland, S., and Etzioni, O. (2011), “Identifying relations for open information extraction”, *Proceedings of the Conference on Empirical Methods in Natural Language Processing*, pp. 1535-1545, Stroudsburg, 2011.

Fahmi, I., Bouma, G., and van der Plas, L. (2007), “Using Multilingual Terms for Biomedical Term Extraction”, *Proceedings of 17th Computational Linguistics in the Netherlands (CLIN)*, pp. 1-8, 2007.

Faure, D., and N´edellec, C. (1998), “A corpus-based conceptual clustering method for verb frames and ontology”, *Proceedings of the LREC Workshop on Adapting lexical and corpus resources to sublanguages and applications,* pp. 5-12, 1998.

Faure, D., and Nédellec, C. (1999), "Knowledge acquisition of predicate argument structures from technical texts using machine learning: The system ASIUM", *Proceedings of the 11th European Workshop (EKAW'99)*, pp. 329-334, Dagstuhl Castle, Germany, 26-29 May 1999.

Faure, D., and Poibeau, T. (2000), "First experiments of using semantic knowledge learned by ASIUM for information extraction task using INTEX", *Proceedings of the ECAI Workshop on Ontology Learning*, pp. 7-12, 2000.

Ferraz, I. N., and Garcia, A. C. B. (2013), "Ontology in association rules", *SpringerPlus*, 2: 452, 2013.

Fortuna, B., Mladenič, D., and Grobelnik, M. (2005), "Semi-automatic Construction of Topic Ontologies", *Proceedings of the Conference on Data Mining and Data Warehouses*, pp. 121-131, Porto, Portugal, 3-7 October 2005.

Fortuna, B. (2011), "Semi-automatic Ontology Construction", Doctor Philosophy, Jožef Stefan International Postgraduate School, Ljubljana.

Fotzo, H., and Gallinari, P. (2004), "Learning generalization specialization relations between concepts—application for automatically building thematic document hierarchies", *Proceedings of the 7th International Conference on Computer-Assisted Information Retrieval (RIAO)*, pp. 1-13, 2004.

Francesconi, E. (2011), "A Learning Approach for Knowledge Acquisition in the Legal Domain", In Approaches to Legal Ontologies, pp. 219-233, Springer Netherlands, 2011.

Frantzi, K., and Ananiadou, S. (1999), "The C-value/NC-value domain independent method for multi-word term extraction", *Journal of Natural Language Processing*, 6(3):145-179, 1999.

Frantzi, K., Ananiadou, S., and Mima, H. (2000), "Automatic recognition of multi-word terms: The Cvalue/NC value method", *International Journal on Digital Libraries*, 3(2): 115-130, 2000.

Frikh, B., Djaanfar, A. S., and Ouhbi, B. (2011), "A New Methodology for Domain Ontology Construction from the Web", *International Journal on Artificial Intelligence Tools*, 20(6): 1157–1170, 2011.

Fuhr, N., (1992), "Probabilistic models in information retrieval", *The Computer Journal - Special issue on information retrieval*, 35(3): 243-255, 1992.

Gacto, M. J., Alcalá, R., and Herrera, F. (2009), "Adaptation and application of multi-objective evolutionary algorithms for rule reduction and parameter tuning of fuzzy rule-based systems", *Soft Computing*, 13(5): 419-436, 2009.

Gaeta, M., Orciuoli, F., Paolozzi, S., and Salerno, S. (2011), "Ontology Extraction for Knowledge Reuse: The e-Learning Perspective", *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans*, 41(4): 798-809, 2011.

Galárraga, L. A., Teflioudi, C., Hose, K., and Suchanek, F. (2013), "AMIE: association rule mining under incomplete evidence in ontological knowledge bases", *Proceedings of the 22nd International Conference on World Wide Web*, pp. 413-422, Geneva, 2013.

Galea, M., and Shen, Q. (2006), "Linguistic Hedges for Ant-generated Rules", *Proceedings of IEEE International Conference on Fuzzy Systems*, pp. 1973-1980, Vancouver, 2006.

Galindo, J. (2008), "Introduction and Trends to Fuzzy Logic and Fuzzy Databases", In Handbook of Research on Fuzzy Information Processing in Databases, Galindo, J. (Ed.), Vol. I, pp. 1-33. Hershey, PA, USA: Information Science Reference (2008)

Gamallo, P., Gonzalez, M., Agustini, A., Lopes, G., and de Lima, V. S. (2002), "Mapping syntactic dependencies onto semantic relations", *Proceedings of the ECAI Workshop on Machine Learning and Natural Language Processing for Ontology Engineering*, pp. 15-22, 2002.

Gharib, T. F., Badr, N., Haridy, S., and Abraham, A. (2012), "Enriching Ontology Concepts Based on Texts from WWW and Corpus", *Journal of Universal Computer Science*, 18(16): 2234-2251, 2012.

Girju, R., and Moldovan, D. (2002), "Text Mining for Causal Relations", *Proceedings of the Fifteenth International Florida Artificial Intelligence Research Society Conference*, pp. 360-364, 2002.

Gomez-Perez, A., and Manzano-Macho, D. (2003), "Deliverable 1.5: A survey of ontology learning methods and techniques", *OntoWeb Consortium, 2003*.

Gomez-Perez, A., Fernandez-Lopez, M., and Corcho-Garcia, O. (2005), "Ontological Engineering With Examples from the Areas of Knowledge Management, e-Commerce and the Semantic Web", Springer London (2005).

Gruber, T. R. (1993), "Towards Principles for the Design of Ontologies Used for Knowledge Sharing", *International Journal Human Computer Studies*, 43 (5-6): 907-928, 1993.

Guarino, N. (1998), "Formal Ontology in Information Systems", *Proceedings of FOIS'98*, pp. 3-15, Trento, Italy, 6-8 June 1998.

Gulla, J. A., and Brasethvik, T. (2008), "A Hybrid Approach to Ontology Relationship Learning", *Proceedings of 13th International Conference on Applications of Natural Language to Information Systems*, pp. 79-90, London, UK, 24-27 June 2008.

Haase, P., and Stojanovic, L. (2005), "Consistent Evolution of OWL Ontologies", *Proceedings of the Second European conference on The Semantic Web: research and Applications*, pp. 182-197, Heraklion, Crete, 29 May – 1 June 2005.

Haase, P., and Völker, J. (2008), "Ontology Learning and Reasoning - Dealing with Uncertainty and Inconsistency", *Proceedings of the ISWC Workshop on Uncertainty Reasoning for the Semantic Web*, pp. 366-384, Galway, Ireland, 7 November 2005.

Hahn, U., and Schnattinger, K. (1998), "Towards text knowledge engineering", *Proceedings of the 15th National Conference on Artificial Intelligence and the 10th Conference on Innovative Applications of Artificial Intelligence (AAAI'98/IAAI'98)*, pp. 524-531, 1998.

Hahn, U., and Schulz, S. (2000), "Towards Very Large Terminological Knowledge Bases: A Case Study from Medicine", *Proceedings of the 13th Biennial Conference of the Canadian Society for Computational Studies of Intelligence*, pp. 176-186, Montéal, Quebec, Canada, 14-17 May 2000.

Hahn, U., and Marko, K. G. (2001), "Joint Knowledge Capture for Grammars and Ontologies", *Proceedings of the First International Conference on Knowledge Capture K-CAP*, pp. 68-75, 2001.

Haiguo, P., Zhixin, W., and Huaqiang, Z. (2009), "Cooperative-PSO-Based PID Neural Network Integral Control Strategy and Simulation Research with Asynchronous Motor Controller Design", *WSEAS Transactions on Circuits and Systems*, 8(8): 696-708, 2009.

Hassan, R., Cohanim, B., and de Weck, O. (2004), "A Comparison of Particle Swarm Optimization and the Genetic Algorithm", *American Institute of Aeronautics and Astronautics*, pp. 1-13, 2004.

Hearst, M. (1992), "Automatic acquisition of hyponyms from large text corpora", *Proceedings of the 14th International Conference on Computational Linguistic (COLING)*, pp. 539-545, Nantes, France, July 1992.

Hearst, M. (1998), "Automated Discovery of WordNet Relations", In WordNet: An Electronic Lexical Database, pp. 132-152, MIT Press, 1998.

Hindle, D. (1990), "Noun Classification from Predicate-Argument Structures", *Proceedings of the 28th annual meeting on Association for Computational Linguistics*, pp. 268-275, 1990.

Hippisley, A., Cheng, D., and Ahmad, K. (2005), "The head-modifier principle and multilingual term extraction", *Journal Natural Language Engineering*, 11(2): 129-157, 2005.

Hofmann, T. (1999), "Probabilistic latent semantic indexing", *Proceedings of the 22nd Annual International ACM SIGIR Conference on Research and development in Information Retrieval*, pp. 50-57, 1999.

Holzinger, A., Yildirim, P., Geier, M., and Simonic, K. (2013), "Quality-Based Knowledge Discovery from Medical Text on the Web", In Quality Issues in the Management of Web Information, pp. 145-158, Springer Berlin Heidelberg, 2013.

Hourali, M., and Montazer, G. A. (2011), "A New Approach for Automating the Ontology Learning Process Using Fuzzy Theory and ART Neural Network", *Journal of Convergence Information Technology (JCIT)*, 6(10): 24-32, 2011.

Hovy, E., and Lin, C. (1999), "Automated Text Summarization in SUMMARIST", *Proceedings of TIPSTER Workshop*, pp. 197-214, Baltimore, Maryland, 13-15 October 1998.

Ijntema, W., Sangers, J., Hogenboom, F., and Frasincar, F. (2012), "A lexico-semantic pattern language for learning ontology instances from text", *Web Semantics: Science, Services and Agents on the World Wide Web*, 15(September 2012): 37–50, 2012.

Ittoo, A., and Bouma, G. (2013), "Term extraction from sparse, ungrammatical domain-specific documents", *Expert Systems with Applications*, 40(1): 2530–2540, 2013.

Jayabarathi, T., Chalasani, S., Shaik, Z. A., and Kodali, N. D. (2007), "Hybrid Differential Evolution and Particle Swarm Optimization Based Solutions to Short Term Hydro Thermal Scheduling", *WSEAS Transactions on Power Systems*, 2(11): 245-254, 2007.

Jiang, X., and Tan, A. (2010), "CRCTOL: A semantic-based domain ontology learning system", *Journal of the American Society for Information Science and Technology*, 61(1): 150–168, 2010.

Jones, S., and Paynter, G. W. (2002), "Automatic extraction of document keyphrases for use in digital libraries: evaluation and applications", *Journal of the American Society for Information Science and Technology*, 53(8): 653-677, 2002.

Jordehi, A. R., and Jasni, J. (2013), "Parameter selection in particle swarm optimisation: a survey", *Journal of Experimental & Theoretical Artificial Intelligence*, 25(4): 527-542, 2013.

Kaufmann, M., Portmann, E., and Fathi, M. (2013), "A concept of semantics extraction from web data by induction of fuzzy ontologies", *Proceedings of the IEEE International Conference on Electro/Information Technology (EIT)*, pp. 1-6, Rapid City, 9-11 May 2013.

Kedzia, P., and Maziarz, M. (2013), "Semantic relation recognition within Polish noun phrase: A rule-based Approach", *Proceedings of International Conference Recent Advances in Natural Language Processing*, pp. 342–349, Hissar, 7-13 September 2013.

Kennedy, J., and Eberhart, R. C. (1995b), "Particle swarm optimization", *Proceeding of The IEEE International Conference on Neural Networks IV*, pp. 1942-1948, Perth, 27 November - 1 December 1995.

Kennedy, J., and Eberhart, R. C. (1997), "A discrete binary version of the particle swarm algorithm", *Proceedings of Computational Cybernetics and Simulation*, pp. 4104–4108, Orlando, 12-15 October 1997.

Kiani, A., and Akbarzadeh, M. R. (2006), "Automatic Text Summarization Using Hybrid Fuzzy GA-GP", *Proceedings of International Conference on Fuzzy Systems*, pp. 977-983, Vancouver, 16-21 July 2006.

Kietz, J. U., Mädche, A., and Volz, R. (2000), "A Method for Semi-automatic Ontology Acquisition from a Corporate Intranet", *Proceedings of In EKAW-2000 Workshop "Ontologies and Text"*, pp. 1-14, Juan-Les-Pins, 2 October 2000.

Kim, J., and Storey, V. C. (2012), "Construction of Domain Ontologies: Sourcing the World Wide Web", In Organizational Efficiency through Intelligent Information Technologies, pp. 68-87, IGI Global, 2012.

Klein, D., and Manning, C. D. (2003), "Accurate unlexicalized parsing", *Proceedings of the 41st Annual Meeting on Association for Computational Linguistics*, Volume 1: 423-430, 2003.

Knijff, J., Meijer, K., Frasincar, F., and Hogenboom, F. (2011), "Word Sense Disambiguation for Automatic Taxonomy Construction from Text-Based Web Corpora", In Web Information System Engineering, pp. 241-248, Springer Berlin Heidelberg, 2011.

Knijff, J., Frasincar, F., and Hogenboom, F. (2013), "Domain taxonomy learning from text: The subsumption method versus hierarchical clustering", *Data & Knowledge Engineering*, 83(2013): 54–69, 2013.

Kozakov, L., Park, Y., Fin, T., Drissi, Y., Doganata, Y., and Cofino, T. A. (2004), "GlossaryExtraction and utilization in the information search and delivery system for IBM technical support", *IBM System Journal*, 43(3): 546-563, 2004.

Kozareva, Z., Riloff, E., and Hovy, E. (2008), "Semantic class learning from the web with hyponym pattern linkage graphs", *Proceedings of ACL-08: HLT*, pp. 1048–1056, 2008.

Kozareva, Z., and Hovy, E. (2010), "A semi-supervised method to learn and construct taxonomies using the web", *Proceedings of the 2010 Conference on Empirical Methods in Natural Language Processing*, pp. 1110–1118, Massachusetts, 9-11 October 2010.

Kumar, A., Lease, M., and Baldridge, J. (2011), "Supervised language modeling for temporal resolution of texts", Proceedings of the 20th ACM international conference on Information and knowledge management, pp. 2069-2072, Glasgow, 24-28 October 2011.

Kumar, V., and Minz, S. (2014), "Multi-Objective Particle Swarm Optimization: An Introduction", *Smart Computing Review*, 4(5): 335-353, 2014.

Kumara, B. T. G. S., Paik, I., Koswatte, K. R. C., and Chen, W. (2014), "Ontology learning with complex data type for Web service clustering", *Proceedings of the IEEE Symposium on Computational Intelligence and Data Mining*, pp. 129 – 136, Orlando, 9-12 December 2014.

Kuo, H., Tsai, T., and Jen-Peng, H. (2006), "Building a Concept Hierarchy by Hierarchical Clustering with Join/Merge Decision", *Proceedings of the 9th Joint Conference on Information Sciences (JCIS)*, pp. 1-4, Kaohsiung, Taiwan, 8-11 October 2006.

Lalwani, S., Singhal, S., Kumar, R., and Gupta, N. (2013), "A comprehensive survey: Applications of multi-objective particle swarm optimization (MOPSO) algorithm", *Transactions on Combinatorics*, 2(1): 39-101, 2013.

Lambert-Torres, G., Carvalho, M. A., da Silva, L. E. B., and Pinto, J. O. P. (2000), "Fitting fuzzy membership functions using genetic algorithms", *Proceedings of Systems, Man and Cybernetics*, pp. 387-392, Nashville, 8-11 October 2000.

Landauer, T., and Dumais, S. T. (1997), "A solution to plato's problem: The latent semantic analysis theory of acquisition, induction and representation of knowledge", *Psychological review*, 104(2):211-240, 1997.

Lau, R. Y. K., Song, D., Li, Y., Cheung, T. C. H., and Hao, J. (2009), "Toward a Fuzzy Domain Ontology Extraction Method for Adaptive e-Learning", *IEEE Transactions on Knowledge and Data Engineering*, 21(6): 800-813, 2009.

Lee, C., Jian, Z., and Huang, L. (2005), "Fuzzy Ontology and Its Application to News Summarization", *IEEE Transactions on Systems, Man, and Cybernetics - Part B: Cybernetics*, 35(5): 859-880, 2005.

Lee, D. (2006), "A Generalized Approach for Analyzing Transportation User Perception Using Fuzzy Sets", Doctor Philosophy, The Pennsylvania State University, Pennsylvania.

Lee, Y, and Kim, C. (2011), "A Learning Ontology Method for RESTful Semantic Web Services", *Proceedings of the IEEE International Conference on Web Services (ICWS)*, pp. 251–258, Washington, DC, 4-9 July 2011.

Lefever, E., Van de Kauter, M., and Hoste, V. (2014), "HypoTerm: Detection of hypernym relations between domain-specific terms in Dutch and English", *Terminology*, 20(2): 250-278, 2014.

Lehmann, J., and Hitzler, P. (2010), "Concept learning in description logics using refinement operators", *Machine Learning*, 78(1-2): 203-250, 2010.

Lehmann, J., Auer, S., Bühmann, L., and Tramp, S. (2011), "Class expression learning for ontology engineering", *Web Semantics: Science, Services and Agents on the World Wide Web*, 9(1):71–81, 2011.

Leong, W. F. (2008), "Multiobjective Particle Swarm Optimization: Integration of Dynamic Population and Multiple-Swarm Concepts and Constraint Handling", Doctor Philosophy, Oklahoma State University, Stillwater.

Lesk, M. (1986), "Automatic sense disambiguation using machine readable dictionaries: How to tell a pine cone from an ice cream cone", *Proceedings of the 5th annual International Conference on Systems Documentation*, pp. 24-26, 1986.

Li, T., Chubak, P., Lakshmanan, L.V.S., and Pottinger, R. (2012), "Efficient Extraction of Ontologies from Domain Specific Text Corpora", *Proceedings of the 21st ACM International Conference on Information and Knowledge Management*, pp. 1537-1541, Maui, 29 October–2 November 2012.

Lin, C. Y., and Hovy, E. (2000), "The Automated Acquisition of Topic Signatures for Text Summarization", *Proceedings of the 18th Conference on Computational Linguistics - Volume 1*, pp. 495-501, 2000.

Lin, D. (1994), "Principar: An efficient, broad-coverage, principle-based parser", *Proceedings of the 15th International Conference on Computational Linguistics*, pp. 482-488, 1994.

Lin, D., and Pantel, P. (2001), "DIRT - Discovery of Inference Rules from Text", *Proceedings of the seventh ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp. 323-328, San Francisco, CA, 2001.

Lin, D., and Pantel, P. (2001), "Induction of Semantic Classes from Natural Language Text", *Proceedings of the seventh ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp. 317-322, 2001.

Lin, D., and Pantel, P. (2002), "Concept Discovery from Text", *Proceedings of the 19th International Conference on Computational Linguistics - Volume 1*, pp. 577-583, 2002.

Lin, D. (2003), "Dependency-Based Evaluation of Minipar", In *Treebanks*, Springer Netherlands, pp. 317-329, 2003.

Lindberg, D. A. B., and Humphreys, B. L. (1993), "The unified medical language system", *Methods of Information in Medicine*, 32(4): 281-291,1993.

Linden, K., and Piitulainen, J. (2004), "Discovering synonyms and other related words", *Proceedings of the 3rd International Workshop on Computational Terminology (CompuTerm)*, pp. 63-70, 2004.

Li-ping, Z., Huan-jun, Y., Shang-xu, H. (2005), "Optimal choice of parameters for particle swarm optimization", *Journal of Zhejiang University Science*, 6(6): 528-534, 2005.

Liu, W. Z. (1996), "An Integrated Approach for Different Attribute Types in Nearest Neighbour Classification", *The Knowledge Engineering Review*, 11(03):245-252, 1996.

Loukachevitch, N., and Nokel, M. (2013), "An Experimental Study of Term Extraction for Real Information-Retrieval Thesauri", *Proceedings 10th International Conference on Terminology and Artificial Intelligence*, pp. 69-76, Villetaneuse, 28–30 October 2013.

Lucanský, M., Šimko, M., and Bieliková, M. (2011), "Enhancing Automatic Term Recognition Algorithms with HTML Tags Processing", *Proceedings of the International Conference on Computer Systems and Technologies*, pp. 173-178, Vienna, 16-17 June 2011.

Maedche, A., and Staab, S. (2000), "Discovering conceptual relations from text", *Proceedings of the 14th European Conference on Artificial Intelligence ECAI*, pp. 321-325, 2000.

Maedche, A., and Staab, S. (2000), "Mining Ontologies from Text", *Proceedings of the 12th European Workshop on Knowledge Acquisition, Modeling and Management*, pp. 189-202, Juan-les-Pins, 2-6 October 2000.

Maedche, A., and Staab, S. (2001), "Ontology learning for the semantic web", *IEEE Intelligent Systems*, 16(2):72-79, 2001.

Maedche, A., and Staab, S. (2002), "Measuring similarity between ontologies", *Proceedings of 13th International Conference on Knowledge Acquisition and Management (EKAW)*, pp. 251-263, Sigüenza, Spain, 1-4 October 2002.

Maedche, A., Pekar, V., and Staab, S. (2003), "Ontology Learning Part One - on Discovering Taxonomic Relations from the Web", *In Web Intelligence*, Ning Zhong.N, Liu.J, Yao, (Eds.), Springer Berlin Heidelberg, pp. 301-319, 2003.

Malo, P., Siitari, P., Ahlgren, O., Wallenius, J., and Korhonen, P. (2010), "Semantic Content Filtering with Wikipedia and Ontologies", *Proceedings of the IEEE International Conference on Data Mining Workshops (ICDMW)*, pp. 518-526, Sydney, 13-13 December 2010.

Mamdani, E. H., and Assilian, S. (1975), "An experiment in linguistic synthesis with a fuzzy logic controller", *International Journal of Man-Machine Studies*, 7(1): 1–13, 1975.

Manda, P., McCarthy, F., and Bridges, S. M. (2013), "Interestingness measures and strategies for mining multi-ontology multi-level association rules from gene ontology annotations for the discovery of new GO relationships", *Journal of Biomedical Informatics*, 46(5):849–856, 2013.

Markert, M., Nissim, M., and Modjeska, N. N. (2003), "Using the Web for Nominal Anaphora Resolution", *Proceedings of EACL Workshop on the Computational Treatment of Anaphora*, pp. 1-8, Budapest, Hungary, 2003.

Maynard, D., Funk, A., and Peters, W. (2009), "Using lexico-syntactic ontology design patterns for ontology creation and population", *Proceedings of the Workshop on Ontology Patterns*, pp. 1-14, 2009.

McNeill, F. M., and Thro, E. (1994), "Fuzzy Logic a Practical Approach", Academic Press Professional (1994).

Medelyan, O., and Witten, I. H. (2005), "Thesaurus-based index term extraction for agricultural documents", *Proceeding of The Sixth Workshop on Agricultural Ontology Service (AOS)*, pp. 1-8, Vila Real, July 2005.

Medelyan, O., Manion, S., Broekstra, J., Divoli, A., Huang, A., and Witten, I. H. (2013), "Constructing a Focused Taxonomy from a Document Collection", In The Semantic Web: Semantics and Big Data, pp. 367-381, Springer Berlin Heidelberg, 2013.

Mendel, J. M. (1995), "Fuzzy Logic Systems for Engineering: A Tutorial", *Proceedings of the IEEE*, 83(3): 345-377, 1995.

Miller, G. A., Beckwith, R., Fellbaum, C., Gross, D., and Miller, K. (1990), "Introduction to WordNet: An on-line lexical database", *International Journal of Lexicography*, 3(4): 235-244, 1990.

Miller, G. A. (1995), "WordNet: A Lexical Database for English", *Communications of the ACM*, 38(11): 39-41, 1995.

Missikoff, M., Navigli, R., and Velardi, P. (2002), "Integrated Approach to Web Ontology Learning and Engineering", *IEEE Computer*, 35(11): 60-63, 2002.

Missikoff, M., Navigli, R., and Velardi, P. (2002), "The Usable Ontology: An Environment for Building and Assessing a Domain Ontology", *Proceedings of First International Semantic Web Conference*, pp. 39-53, Sardinia, Italy, 9-12 June, 2002.

Moore, J., and Chapman, R. (1999), "Application of particle swarm to multiobjective optimization", Technical report, Department of Computer Science and Software Engineering, Auburn University, 1999.

Morik, K. (1993), "Balanced Cooperative Modelling", *Machine Learning*, 11(2-3): 217-235, 1993.

Morin, E. (1999), "Automatic acquisition of semantic relations between terms from technical corpora". *Proceedings of the Fifth International Congress on Terminology and Knowledge Engineering*, 1999.

Mukaidono, M. (2004), "Fuzzy logic for Beginners", World Scientific Publishing (2004).

Mustapha, N. B., Zghal, H. B., Aufaure, M., and Ghezala, H. B. (2009), "Survey on Ontology learning from Web and open issues", *Proceedings of Third International Symposium on Innovation in Information & Communication Technology*, pp. 1-10, Amman, Jordan, 15-17 December 2009.

Muthukaruppan, S., and Er, M. J. (2012), "A hybrid particle swarm optimization based fuzzy expert system for the diagnosis of coronary artery disease", *Expert Systems with Applications*, 39(14): 11657–11665, 2012.

Navigli, R., and Velardi, P. (2002), "Semantic Interpretation of Terminological Strings", *Proceedings of 6$^{th}$ International Conference on Terminology and Knowledge Engineering*, pp. 95-100, Vandoeuvre-lès-Nancy, France, August 2002.

Navigli, R., Velardi, P., and Gangemi, A. (2003), "Ontology Learning and its application to automated terminology translation", *IEEE Intelligent Systems*, 18(1): 22-31, 2003.

Navigli, R., and Velardi, P. (2004), "Learning domain ontologies from document warehouses and dedicated web sites", *Journal of Computational Linguist*ics, 30(2): 151-170, 2004.

Navigli, R., and Lapata, M. (2010), "An Experimental Study of Graph Connectivity for Unsupervised Word Sense Disambiguation", *IEEE Transactions on Pattern Analysis and Machine Intelligence,* 32(4): 678 – 692, 2010.

Navigli, R., Velardi, P., and Faralli, S. (2011), "A Graph-based Algorithm for Inducing Lexical Taxonomies from Scratch", *Proceedings of the Twenty-Second international joint conference on Artificial Intelligence*, pp. 1872-1877, 2011.

Navigli, R., and Ponzetto, S. P. (2012), "BabelNet: The automatic construction, evaluation and application of a wide-coverage multilingual semantic network", *Artificial Intelligence*, 193(2012): 217–250, 2012.

Nazri, M. Z. A., Shamsudin, S. M., Bakar, A. A., and Ghani, T. A. (2008), "Using Linguistic Patterns in FCA-Based Approach for Automatic Acquisition of Taxonomies from Malay Text", *Proceedings of International Symposium on Information Technology*, pp. 1-7, Kuala Lumpur, Malaysia, 26-28 August 2008.

Nazri, M. Z. A., Shamsuddin, S. M., Bakar, A. A., and Abdullah, S. (2009), "A Hybrid Approach for Learning Concept Hierarchy from Malay Text Using GAHC and Immune Network", *Proceedings of 8th International Conference, ICARIS 2009*, pp 315-328, York, UK, 9-12 August 2009.

Nazri, M. Z. A., Shamsudin, S. M., and Bakar, A. A. (2010), "Clonal Selection Algorithm for Learning Concept Hierarchy from Malay Text", *Proceedings of 5th International Conference Rough Set and Knowledge Technology*, pp. 453-461, Beijing, China, 15-17 October 2010.

Nazri, M. Z. A. (2011), "Taxonomy Learning from Malay Texts Using Artificial Immune System Based Clustering", Doctor Philosophy, Universiti Teknologi Malaysia, Skudai.

Nazri, M. Z. A., Shamsuddin, S. M., Bakar, A. A., and Abdullah, S. (2011), "A hybrid approach for learning concept hierarchy from Malay text using artificial immune network", *International Journal of Natural Computing*, 10(1): 275-304, 2011.

Nebot, V., and Berlanga, R. (2012), "Finding association rules in semantic web data", *Knowledge-Based Systems*, 25(1): 51–62, 2012.

Nedellec, C. (2000), "Corpus-Based Learning of Semantic Relations by the ILP System, Asium", *In Learning Language in Logic*, Springer Berlin Heidelberg, pp. 259-278, 2000.

Neshati, M., Alijamaat, A., Abolhassani, H., Rahimi, A., and Hoseini, M. (2007), "Taxonomy Learning Using Compound Similarity Measure", *Proceedings of IEEE/WIC/ACM International Conference on Web Intelligence*, pp. 487-490, Fremont, CA, 2-5 November 2007.

O'Hara, T., Mahesh, K., and Nirenburg, S. (1998), "Lexical acquisition with WordNet and the microkosmos ontology", *Proceedings of the Coling-ACLWorkshop on Usage ofWordNet in Natural Language Processing Systems, pp. 94-101, 1998.*

Panchenko, A., Adeykin, S., Romanov, A., and Romanov, P. (2012), "Extraction of Semantic Relations between Concepts with KNN Algorithms on Wikipedia", *Proceedings of Concept Discovery in Unstructured Data Workshop (CDUD) of 10th International Conference on Formal Concept Analysis*, pp. 78-86, Leuven, 10 May 2012.

Panel, P., and Lin, D. (2001), "A statistical corpus-based TermExtractor", *Proceedings of the 14th Biennial Conference of the Canadian Society on Computational Studies of Intelligence: Advances in Artificial Intelligence*, pp. 36-46, Ottawa, 7-9 June 2001.

Pantel, P., and Pennacchiotti, M. (2006), "Espresso: A Bootstrapping Algorithm for Automatically Harvesting Semantic Relations", *Proceedings of the 21st International Conference on Computational Linguistics*, pp. 113-120, Sydney, Australia, 2006.

Park, Y., Byrd, R. J., and Boguraev, B. K. (2002), "Automatic glossary extraction: Beyond terminology identification". *Proceedings of The 19th International Conference on Computational Linguistics*, pp. 772-778, Stroudsburg, 26-30 August 2002.

Parsopoulos, K. E., and Vrahatis, M. N. (2002), "Recent approaches to global optimization problems through particle swarm optimization", *Natural Computing*, 1(2-3): 235-306, 2002.

Parsopoulos, K. E., and Vrahatis, M. N. (2008), "Multi-Objective Particles Swarm Optimization Approaches", In Multi-Objective Optimization in Computational Intelligence: Theory and Practice, pp. 20-42, IGI Global, 2008.

Pasca, M. (2004), "Acquisition of categorized named entities for web search", *Proceedings of the thirteenth ACM International Conference on Information and Knowledge Management*, pp. 137-145, 2004.

Paslaru, E., Simperl, B., and Tempich, C. (2006), "Ontology Engineering: A Reality Check", *Proceedings of 5th International Conference on Ontologies, Databases and Applications of Semantics*, pp. 836-854, Montpellier, France, 29 October – 3 November 2006.

Patel, P. B., and Marwala, T. (2011), "Fuzzy Inference Systems Optimization", *Proceedings of First International Conference on Integrated Computing Technology*, pp. 1-21, 2011.

Patel, P. B., and Marwala, T. (2012), "Optimization of Fuzzy Inference System Field Classifiers Using Genetic Algorithms and Simulated Annealing", *Proceedings of 13th International Conference*, EANN, pp. 21-30, London, UK, 20-23 September 2012.

Paukkeri, M., García-Plaza, A. P., Fresno, V., Unanu, R. M., and Honkela, T. (2012), "Learning a taxonomy from a set of text documents", *Applied Soft Computing*, 12(3): 1138-1148, 2012.

Pedersen, T., Patwardhan, S., and Michelizzi, J. (2004), "WordNet:similarity: Measuring the relatedness of concepts", *Proceedings of the Demonstration Papers at the Conference of the North American Chapter of the Association for Computational and Linguistics: Human Language Technologies (HLT-NAACL)*, pp. 38-14, 2004.

Pedersen, T. (2010), "Information content measures of semantic similarity perform better without sense-tagged text", *The 2010 Annual Conference of the North American Chapter of the Association for Computational Linguistics*, pp. 329-332, Los Angeles, 2-4 June 2010.

Pedersen, T. (2012), "Duluth: measuring degrees of relational similarity with the gloss vector measure of semantic relatedness", *Proceedings of the First Joint Conference on Lexical and Computational Semantics*, pp. 497-501, Montreal, 7-8 June 2012.

Pereira, F., Tishby, N., and Lee, L. (1993), "Distributional clustering of English words", *Proceedings of the 31st annual meeting on Association for Computational Linguistics*, pp. 183-190, 1993.

Petasis, G., Karkaletsis, V., Paliouras, G., Krithara, A., and Zavitsanos, E. (2011), "Ontology Population and Enrichment: State of the Art", *Knowledge-Driven Multimedia Information Extraction and Ontology Evolution, Lecture Notes in Computer Science*, Volume 6050, pp. 134-166, 2011.

Pinnis, M., Ljubešić, N., Ştefănescu, D., Skadiņa, I., Tadić, M., and Gornostay, T. (2012), "Term Extraction, Tagging, and Mapping Tools for Under-Resourced Languages", *Proceedings of the 10th Terminology and Knowledge Engineering Conference*, pp.193-208, Madrid, 19-22 June 2012.

Pinto, H. S., and Martins, J. P. (2004), "Ontologies: How can they be built?" *Knowledge and Information Systems,* 6(4): 441 464, 2004.

Ponte, J. M., and Croft, W. B. (1998), "A language modeling approach to information retrieval", *Proceedings of the 21st Annual International ACM SIGIR Conference on Research and Development in Information Retrieval*, 275-281, 1998.

Ponzetto, S. P., and Navigli, R. (2010), "Knowledge-rich Word Sense Disambiguation rivaling supervised systems", *Proceedings of the 48th Annual Meeting of the Association for Computational Linguistics*, pp. 1522-1531, Uppsala, 11-16 July 2010.

Punuru, J., and Chen, J. (2012), "Learning non-taxonomical semantic relations from domain texts", *Journal of Intelligent Information Systems*, 38(1): 191-207, 2012.

Quan, T. T., Hui, S. C., Hoang, T., Thanh, C., Quan, T., Hui, S. C., and Cao, T. H. (2004), "A Fuzzy FCA-based Approach to Conceptual Clustering for Automatic Generation of Concept Hierarchy on Uncertainty Data", *Proceedings of CLA Conference*, pp. 1-12, 2004.

Ratsch, E., Schultz, J., Saric, J., Lavin, P. C., Wittig, U., Reyle, U., and Rojas, I. (2003). "Developing a protein interactions ontology", *Comparative and Functional Genomics,* 4(l): 85-89, 2003.

Reinberger, M., and Spyns, P. (2005), "Unsupervised Text Mining for the Learning of DOGMA inspired Ontologies", In Ontology Learning from Text: Methods, Applications and Evaluation, pp. 1-15, IOS Press, 2005.

Resnik, P. (1999), "Semantic similarity in a taxonomy: An information-based measure and its application to problems of ambiguity in natural language", *Journal of Artificial Intelligence Research*, 11(1): 95–130, 1999.

Reveiz, H. A., and Carlos, E. L. R. (2009), "Operational Risk Management using a Fuzzy Logic Inference System", In Borradores de economía Number: 574, pp. 1-30, Banco de la República, 2009.

Reyes-Sierra, M., and Coello, C. A. C. (2006), "Multi-Objective Particle Swarm Optimizers: A Survey of the State-of-the-Art", *International Journal of Computational Intelligence Research*, 2(3): 287–308, 2006.

Rini, D. P., Shamsuddin, S. M., and Yuhaniz, S. S. (2011), "Particle Swarm Optimization: Technique, System and Challenges", *International Journal of Computer Applications,* 14(1): 19-27, 2011.

Rini, D. P., Shamsuddin, S. M., and Yuhaniz, S. S. (2014), "Particle swarm optimization for ANFIS interpretability and accuracy", *Soft Computing*, Springer Berlin Heidelberg, pp. 1-12, 2014.

Ruiz-Martínez, J. M., Valencia-García, R., Fernández-Breis, J. T., García-Sánchez, F., and Martínez-Béjar, R. (2011), "Ontology learning from biomedical natural language documents using UMLS", *Expert Systems with Applications*, 38(10): 12365-12378, 2011.

Ryu, P., and Choi, K. (2005), "An Information-Theoretic Approach to Taxonomy Extraction for Ontology Learning", *In: Ontology Learning from Text: Methods, Evaluation and Applications*, pp. 15-28, IOS Press, 2005.

Salton, G., and Buckley, C. (1988), "Term-weighting approaches in automatic text retrieval", *Information Processing & Management*, 24: 515-523, 1988.

Sánchez, D., Isern, D., and Millan, M. (2010), "Content annotation for the semantic web: an automatic web-based approach", *Knowledge and Information Systems*, 27(3): 393-418, 2010.

Sánchez, D., Moreno, A., and Vasto-Terrientes, L. D. (2012), "Learning relation axioms from text: An automatic Web-based approach", *Expert Systems with Applications*, 39(5): 5792–5805, 2012.

Sanderson, M., and Croft, B. (1999), "Deriving concept hierarchies from text", *Proceedings of the 22nd annual ACM SIGIR Conference on Research and Development in Information Retrieval*, pp. 206-213, 1999.

Santoso, H. A., Haw, S., and Abdul-Mehdi, Z. T. (2011), "Ontology extraction from relational database: Concept hierarchy as background knowledge", *Knowledge-Based Systems*, 24(3): 457-464, 2011.

Saruladha, K., Aghila, G., and Raj, S. (2010), "A New Semantic Similarity Metric for Solving Sparse Data Problem in Ontology based Information Retrieval System", *International Journal of Computer Science Issues*, 7(3): 40-48, 2010.

Schmid, H. (1994), "Probabilistic part-of-speech tagging using decision trees", *Proceedings of the International Conference on New Methods in Language Processing*, pp. 1-9, Manchester, UK, 1994.

Schoening, J. (2003), "Standard Upper Ontology Working Group (SUO WG)", 2003.

Schutz, A., and Buitelaar, P. (2005), "Relext: A tool for relation extraction from text in ontology extension," *Proceedings of 4th International Semantic Web Conference*, pp. 593-606, Galway, Ireland, 6-10 November 2005.

Sclano, F., and Velardi, P. (2007), "Termextractor: a web application to learn the shared terminology of emergent web communities", *Proceedings of the 3rd International Conference on Interoperability for Enterprise Software and Applications (I-ESA)*, pp. 287-298, Funchal, 28-30 March 2007.

Sekine, S., and Grishman, R. (1995), "A Corpus-based Probabilistic Grammar with Only Two Non-terminals", *Proceedings of Fourth International Workshop on Parsing Technologies*, pp. 1-8, 1995.

Senellart, P. P., and Blondel, V. D. (2003), "Automatic discovery of similar words", *In Survey of Text Mining*, pp. 1-20, Springer-Verlag Berlin, 2003.

Serra, I., Girardi, R., and Novais, P. (2014), "Evaluating techniques for learning non-taxonomic relationships of ontologies from text", *Expert Systems with Applications*, 41(11): 5201–5211, 2014.

Shamsfard, M., and Barforoush, A. A. (2002), "An introduction to HASTI: an ontology learning system", *Proceedings of 6th Conference on Artificial Intelligence and Soft Computing*, Banff, Canada, June 2002.

Shamsfard, M., and Barforoush, A. A. (2003), "The State of the Art in Ontology Learning: A Framework for Comparison", *The Knowledge Engineering Review*, 18(4): 293-316, 2003.

Shamsfard, M. (2010), "Lexico-syntactic and Semantic Patterns for Extracting Knowledge from Persian Texts", *International Journal on Computer Science and Engineering*, 2(6): 2190-2196, 2010.

Shi, Y., and Eberhart, R. C. (1998), "A Modified Particle Swarm Optimizer", *Proceedings of The 1998 IEEE International Conference on Evolutionary Computation*, pp. 69–73, Anchorage, 4-9 May 1998.

Shi, Y., and Eberhart, R. C. (1999), "Empirical study of particle swarm optimization", *Proceedings of the 1999 Congress on Evolutionary Computation*, pp. 1945-1950, Washington, DC, 6-9 July 1999.

Simko, M., and Bielikova, M. (2012), "Discovering Hierarchical Relationships in Educational Content", In Advances in Web-Based Learning, pp. 132-141, Springer Berlin Heidelberg, 2012.

Sleator, D. D., and Temperley, D. (1993), "Parsing English with a link grammar", *Proceedings of the 3rd International Workshop on Parsing Technologies*, pp. 1-14, 1993.

Snow, R., Jurafsky, D., and Ng, A. Y. (2005), "Learning syntactic patterns for automatic hypernym discovery", *Proceedings of the 17$^{th}$ Conference on Advances in Neural Information Processing Systems*, pp. 1-8, Vancouver, British Columbia, 13-18 December 2004.

Sombatsrisomboon, R., Matsuo, Y., and Ishizuka, M. (2003), "Acquisition of hypernyms and hyponyms from the WWW", *Proceedings of the 2nd International Workshop on Active Mining*, pp. 1-6, 2003.

Spanakis, G., Siolas, G., and Stafylopatis, A. (2012), "Exploiting Wikipedia Knowledge for Conceptual Hierarchical Clustering of Documents", *The Computer Journal*, 55(3): 299-312, 2012.

Spiliopoulou, M., Rinaldi, F., Black, W. J., Zarri, G. P., Mueller, R., and Brunzel, M. (2004), "Coupling Information Extraction and Data Mining for Ontology Learning in PARMENIDES", *Proceedings of the 7th International Conference on Computer-Assisted Information Retrieval*, pp. 1-14, 2004.

Srikant, R., and Agrawal, R. (1997), "Mining generalized association rules", *Future Generation Computer Systems*, 13(2-3): 161–180, 1997.

Steinbach, M., Klooster, S., Tan, P., Potter, C., and Kumar, V. (2002), "Temporal Data Mining for the Discovery and Analysis of Ocean Climate Indices", *Proceedings of the KDD Temporal Data Mining Workshop*, pp. 1-12, 2002.

Stranieri, A., and Zeleznikow, J. (2005), "Uncertain and Statistical Data Mining", *In Knowledge Discovery from Legal Databases*, Springer Netherlands, pp. 99-128, 2005.

Stranieri, A., and Zeleznikow, J. (2006), "Knowledge Discovery from Legal Databases – Using Neural Networks and Data Mining to Build Legal Decision Support Systems", *In Information Technology and Lawyers*, Springer Netherlands, pp 81-117, 2006.

Strehl, A. (2002), "Relationship-based clustering and cluster ensembles for high-dimensional data mining", Ph.D. dissertation, University of Texas at Austin, 2002.

Stumme, G., Ehrig, M., Handschuh, S., Hotho, A., Maedche, A., and Motik, B. (2003), "The Karlsruhe View on Ontologies", *Technical Report University of Karlsruhe*, Institute AIFB, 2003.

Sun, H., Fan, W., and Chai, Y. (2012), "An ontology enabled runtime infrastructure", *Proceedings of the IEEE 16th International Conference on Computer Supported Cooperative Work in Design (CSCWD)*, pp. 483-490, Wuhan, 23-25 May 2012.

Taba, L. S., and Caseli, H. M. (2012), "Automatic Hyponymy Identification from Brazilian Portuguese Texts", In Computational Processing of the Portuguese Language, pp. 186-192, Springer Berlin Heidelberg, 2012.

Terwijn, S. A., Torenvliet, L., and Vitanyi, P. M. B. (2011), "Nonapproximability of the normalized information distance", *Journal of Computer and System Sciences*, 77(4): 738-742, 2011.

Tsatsaronis, G., Varlamis, I., and Vazirgiannis, M. (2010), "Text Relatedness Based on a Word Thesaurus", *Journal of Artificial Intelligence Research*, 37(2010): 1-39, 2010.

Tsuruoka, Y., and Tsujii, J. (2005), "Bidirectional Inference with the Easiest-First Strategy for Tagging Sequence Data", *Proceedings of the Conference on Human Language Technology and Empirical Methods in Natural Language Processing*, pp. 467-474, 2005.

Tu, X., He, T., Chen, L., Luo, J., and Zhang, M. (2010), "Wikipedia-Based Semantic Smoothing for the Language Modeling Approach to Information Retrieval", In Advances in Information Retrieval, pp. 370-381, Springer Berlin Heidelberg, 2010.

Turcato, D., Popowich, F., Toole, J., Fass, D., Nicholson, D., and Tisher, G. (2000), "Adapting a Synonym Database to Specific Domains", *Proceedings of the ACL-2000 workshop on Recent Advances in Natural Language Processing and Information Retrieval*, 11: 1-11, Hong Kong, 2000.

Turney, P. D. (2000), "Learning algorithms for keyphrase extraction", *Journal of Information Retrieval*, 2(4): 303–336, 2000.

Turney, P. D. (2001), "Mining the web for synonyms: PMI-IR versus LSA on TOEFL", *Proceedings of the 12th European Conference on Machine Learning*, pp. 491-502, Freiburg, Germany, 2001.

Turney, P. D., and Pantel, P. (2010), "From Frequency to Meaning: Vector Space Models of Semantics", *Journal of Artificial Intelligence Research*, 37(2010): 141-188, 2010.

Van de Cruys, T. (2011), "Two multivariate generalizations of pointwise mutual information", *Proceedings of the Workshop on Distributional Semantics and Compositionality*, pp. 16-20, Portland, 24 June 2011.

Vargas-Vera, M., Domingue, J., Kalfoglou, Y., Motta, E., and Shum, S. B. (2001), "Template-driven information extraction for populating ontologies", Proceedings of *IJCAI Workshop on Ontology Learning, pp. 1-7 Seattle, WA, USA,* August 2001.

Vela, M., and Declerck, T. (2011), "A Multi-Layer Approach to the Derivation of Schema Components of Ontologies from German Text", *Proceedings of the Fifth International Conference on Advances in Semantic Processing*, pp. 91-96, Lisbon, 20-25 November 2011.

Velardi, P., Navigli, R., Cucchiarelli, A., and Neri, F. (2005), "Evaluation of OntoLearn, a methodology for automatic population of domain ontologies", In Ontology Learning from Text: Methods, Applications and Evaluation, pp. 92-106, IOS Press, 2005.

Velardi, P., Faralli, S., and Navigli, R. (2013), "OntoLearn Reloaded: A Graph-Based Algorithm for Taxonomy Induction", *Computational Linguistics*, 39(3): 665-707, 2013.

Veronis, J., and Ide, N. (1998), "Word sense disambiguation: The state of the art", *Computational Linguistics*, 24(1): 1–41, 1998.

Vitanyi, P. M. B., Balbach, F. J., Cilibrasi, R. L., and Li, M. (2009), "Normalized Information Distance", *In Information Theory and Statistical Learning*, pp. 45-82, Springer, 2009.

Wang, L. -X., and Mendel, J. M. (1992), "Generating Fuzzy Rules by Learning from Examples", *IEEE Transactions on Systems, Man, and Cybernetics*, 22(6): 1414–1427, 1992.

Wang, T., and Hirst, G. (2011), "Refining the notions of depth and density in WordNet-based semantic similarity measures", *Proceedings of the Conference on Empirical Methods in Natural Language Processing*, pp. 1003-1011, Edinburgh, 27-31 July 2011.

Wang, W., Barnaghi, P., and Bargiela, A. (2010), “Probabilistic Topic Models for Learning Terminological Ontologies”, *IEEE Transactions on Knowledge and Data Engineering*, 22(7): 1028–1040, 2010.

Wei, Y., Wang, R., Hu, Y., and Wang, X. (2012), “From Web Resources to Agricultural Ontology: a Method for Semi-Automatic Construction”, *Journal of Integrative Agriculture*, 11(5): 775–783, 2012.

Weichselbraun, A., Wohlgenannt, G., and Scharl, A. (2010), “Refining non-taxonomic relation labels with external structured data to support ontology learning”, *Journal Data & Knowledge Engineering*, 69(8): 763-778, 2010.

Wermter, J., and Hahn, U. (2005), “Finding New Terminology in Very Large Corpora”, *Proceedings of the 3rd International Conference on Knowledge Capture*, pp. 137-144, 2005.

Widdows, D. (2003), “Unsupervised Methods for Developing Taxonomies by Combining Syntactic and Statistical Information”, *Proceedings of the Conference of the North American Chapter of the Association for Computational Linguistics on Human Language Technology*, 1: 197-204, 2003.

Wielinga, B. J., Schreiber, A. T., Wielemaker, J., and Sandberg, J. A. C. (2001), “From Thesaurus to Ontology”, *Proceedings of the 1st International Conference on Knowledge Capture*, pp. 194-201, Columbia, Canada, 2001.

Witten, I. H., Paynter, G. W., Frank, E., Gutwin, C., and Nevill-Manning, C. G. (1999), “KEA: Practical automatic keyphrase extraction”, *Proceedings of The Fourth ACM Conference on Digital Libraries*, pp. 254-256, Berkeley, California , 11-14 August 1999.

Wong, W., Liu, W., and Bennamoun, M. (2012), “Ontology Learning from ext: A Look Back and into the Future”, *ACM Computing Surveys*, 44(4): 20:1-20:36, 2012.

Wu, H., and Fang, H. (2012), “Relation Based Term Weighting Regularization”, In Advances in Information Retrieval, pp. 109-120, Springer Berlin Heidelberg, 2012.

Xu, F., Kurz, D., Piskorski, J., and Schmeier, S. (2002), “A Domain Adaptive Approach to Automatic Acquisition of Domain Relevant Terms and their Relations with Bootstrapping”, *Proceedings of the third International Conference on Language Resources and Evaluation*, pp. 1-7, Las Palmas, Canary Island, Spain, May 2002.

Xue, B., Zhang, M., and Browne, W. N. (2012), “Particle Swarm Optimization for Feature Selection in Classification: A Multi-Objective Approach”, *IEEE Transactions on Cybernetics*, 43(6): 1656–1671, 2012.

Yang, X. S. (2008), “Nature-Inspired Metaheuristic Algorithms”, 1st Edition, Luniver Press (2008).

Yang, Y., and Calmet, J. (2005), “OntoBayes: An ontology-driven uncertainty model”, *Proceedings of the International Conference on Intelligent Agents, Web Technologies and Internet Commerce*, pp. 457-463, Vienna, 28-30 November 2005.

Yates, R. B., and Ribeiro-Neto, B. (1999), “Modern Information Retrieval”, 1st Edition., Addison-Wesley (1999).

Yeh, J., and Sie, S. (2006), “Towards Automatic Concept Hierarchy Generation for Specific Knowledge Network”, *Proceedings of 19th International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems*, pp. 982-989, Annecy, France, 27-30 June 2006.

Yu, L., Wu, C., Chang, R., Liu, C., and Hovy, E. (2010), “Annotation and verification of sense pools in OntoNotes”, *Information Processing & Management*, 6(4): 436–447, 2010.

Zadeh, L. A. (1973), “Outline of a New Approach to the Analysis of Complex Systems and Decision Processes”, *IEEE Transactions on Systems, Man, and Cybernetics*, SMC-3(1): 28-44, 1973.

Zahedi, M., and Kahani, M. (2013), “SREC: Discourse-level semantic relation extraction from text”, *Neural Computing and Applications*, 23(6): 1573-1582, 2013.

Zavitsanos, E., Paliouras, G., Vouros, G. A., and Petridis, S. (2010), “Learning Subsumption Hierarchies of Ontology Concepts from Texts”, *Web Intelligence and Agent Systems*, 8(1): 37-51, 2010.

Zavitsanos, E., Paliouras, G., and Vouros, G. A. (2011), “Gold Standard Evaluation of Ontology Learning Methods through Ontology Transformation and Alignment”, *IEEE Transactions on Knowledge and Data Engineering*, 23(11):1635-1648, 2011.

Zeng, X., and Singh, M. G. (1996), “A relationship between membership functions and approximation accuracy in fuzzy systems”, *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, 26(1): 176-180, 1996.

Zhang, Z., Iria, J., Brewster, C., and Ciravegna, F. (2008), “A Comparative Evaluation of Term Recognition Algorithms”, *Proceedings of The sixth international conference on Language Resources and Evaluation,* pp. 2108- 2113, Marrakech, Morocco, 28 – 31 May 2008.

Zhao, L., and Ichise, R. (2012), “Mid-Ontology Learning from Linked Data”, *In The Semantic Web*, pp. 112-127, Springer Berlin Heidelberg, 2012.

Zhao, Y., and Li, B. (2007), “A New Method for Optimizing Fuzzy Membership Function”, *Proceedings of International Conference on Mechatronics and Automation*, pp. 674-678, Harbin, China, 5-8 August 2007.

Zhou, L. (2007), “Ontology learning: state of the art and open issues”, *Information Technology and Management*, 8(3): 241-252, 2007.

Zong, N., Im, D., Yang, S., Namgoon, H., and Kim, H. (2012), “Dynamic generation of concepts hierarchies for knowledge discovering in bio-medical linked data sets”, *Proceedings of the 6th International Conference on Ubiquitous Information Management and Communication*, pp. 1-5 , Kuala Lumpur, 20-22 February 2012.