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IMPROVING SEMANTIC PROPERTIES RELATIONSHIPS EXTRACTION IN ONTOLOGY EVOLUTION

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ABSTRACT

The ontology allows enriching the structure meaning for RDF data. It is necessary to explicitly impose formal interpretation that leads to a unified understanding of the meaning of these data. Exploring non-taxonomic relationships helps in building a mature ontology. The existing studies show some challenges to extract the semantic properties relationship from the ontologies. The study intends to develop a novel technique for semantic properties relationship extraction. It deliberates observing link intersections within domain individuals. That is, a parallel process is proposed to scale the performance of generating context-aware domain-independent routine. The proposed model follows a bottom-up approach to nominate non-taxonomic relationships using Natural Language Processing (NLP) and heuristics through three major phases, semantic-based bulk processing, relationship mining, and relationship evolution. The evaluation metrics include accuracy, precision, recall, and F-measure are employed for evaluating the proposed approach's efficiency, which shows promising outcomes. The outcome of the study suggests that NLP based heuristics assist the relationship extraction process. Moreover, this work discusses some recommendations for future research directions.

Keywords: *Ontology, Natural Language Processing, Non- Taxonomic Relationship, Relationship Mining, Web Semantics*

1. INTRODUCTION

Formally structured representation of massive data in different formats resulted in introducing the Semantic Web vision [1],[2]. The semantic modeling allows the meaning of the data to be available, formally, with the data. Resource Descriptive Framework (RDF) models the data into a simple structure (called triple), namely <Subject, Predicate, Object> <S,P,O> entities, in order to better managing, structuring, and reason about the data. Semantic framing (or simply schema) of the data, that is represented in RDF format, can be determined by shared concepts and set of relationships. Targeting lost or missed important facts is considered an attempt to a complete state of a given Knowledge Graphs (KGs) [3]. Technologies, such as RDF-Schema or Ontology, would provide a formal and shared understanding of a given domain and progress semantic interoperability, advancing labeled graph formal representations [2],[4],[5],[6],[7]. Data in isolation state and processing them independently would hinder the utilization of the advancement semantics modeling (semantic heterogeneity) [8],[9]. Data needs to be crafted into a simple machine-understandable structure, i.e., RDF. That is, careful adaptation steps are necessary to manipulate multiple formats from different resources with a different meaning. Individuals are essential recourses components that are placed within classes. These resources are things that Ontology describes. In semantic web technologies, a unique Uniform Resource Identifier (URI) for each entity is published. In the <S,P,O> triple, the

```
1: <?xml version="1.0"?>
2: <rdf:RDF
xmlns:rdf="http://www.w3.org/1999/0
2/22-rdf-syntax-ns#"
3:   xmlns:
ex="http://example.com/1.1/">
4:   <rdf:Description
rdf:about="http://www.hospital.com/
Patients/patient1">
5:     <ex:Name> Smith </ex:Name>
6:   </rdf:Description>
7: </rdf:RDF>
```

object can be URI, literal, or simply a blank node as shown in figure 1. Relationship extraction is a sub-task of knowledge extraction aimed at semantic relations in texts. Data in machine-readable formats can be used for various applications requiring standardized syntactic and semantic expertise. In view of these vast volumes of data, people need to understand better the key issues and details. In certain instances, they may want details of main entities and principles and their relationships. The extraction of such relationships from the distributed data entities is a complex task. A new object should be linked to previous objects or historical records that provide relevant information. It is therefore important that the various aspects of data are analyzed and examined to satisfy the demand of individuals. A Resource Description Framework (RDF) defines a relationship between two objects. For instance, figure 2 reflects a Resource RDF graph.

Figure 1: RDF syntax example

Figure 2: RDF graphical representation example

In this example, the statement states that "the name of the patient is Smith." A triple represents a relationship where more than one triple are semantically connected forming which is called a RDF Graph [10].

These technologies would allow inferring further information from plainly itemized information and add extensive inferencing capabilities. Moreover, semantic modeling promotes intelligence sharing, browsing, and searching. Shift thinking to empower the data into a semantically structured format would significantly improve the processing power and allow other perceptions about the data [11],[12],[2],[13],[14]. A standard semantic query language called Simple Protocol and RDF Query Language (SPARQL) would semantically query not only data but semantic schema. SPARQL technology has the ability to query different data repositories that support the notation of data integration and infer semantically-modeled graphs [5],[15]. These data in this semantic model can be re-purposed and allow imposing the semantic awareness of implicit resources. To end this, these data should be semantical inter and intra-related explicitly and implicitly.

The vast expansion of the structured semantic-based data of the Linked Open Data (LOD) cloud with 1,255 datasets and 16,174 links are shown in figure 3. One of the current advanced projects is "DBpedia" and part of LOD. It is a community-based initiative to extract standardized knowledge from various Wikimedia projects and consists of 21 billion triples and available in 125 languages [16],[17],[18]. DBpedia facilitates a massive amount of knowledge from Wikimedia projects. This organized information is like an open knowledge graph (OKG) [19],[20]. DBpedia enables public access to structured data referred to as the Linked Open Data Cloud where live web query and inferencing services through ad-hoc and federated SPARQL [21],[22]. Moreover, the semantic-based data in the recent development lead to technologies that facilitate enterprise semantic graph Ontotext GraphDB and Stardog are some of the data platforms dedicated to connecting data across enterprises. They are based on the W3C standards, provide firm SPARQL queries, facilitate RDF triple stores through core functionalities for data integration and cross-enterprise data publishing activities[23],[24],[25].

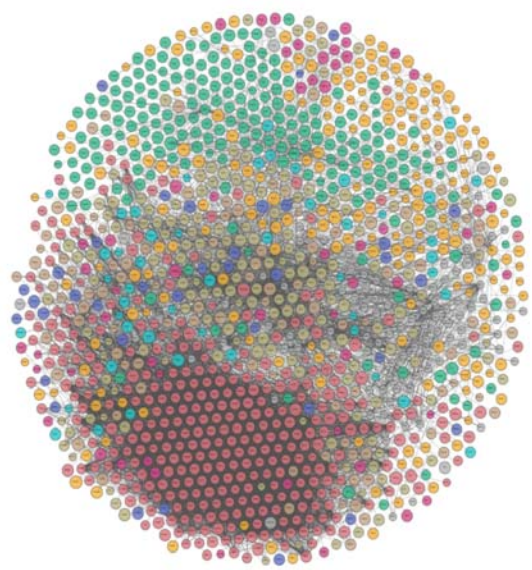

Figure 3: Linked Open Data Cloud

One of the most vital strength points of this technology is connecting entities via their meaning. This allows drawing connections that are more precise between entities. Ontologies play a critical role in the LOD cloud [26],[27]. To learn ontology, three approaches are there manual, semi-automated, and automated. The major difference among them is the level of the human factor involvement [28],[29],[30]. Taxonomic and non-taxonomic relationships are the ways to define relationship representation of the ontology formally. As defined by [31], it is a "formal, explicit specification of a

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shared conceptualization." It allows various applications to share well-defined conceptualization. Ontology mainly consists of Classes (or Concepts), Relationships that include taxonomic and non-taxonomic relationships, Instances (or Individuals), and finally, Axioms [32]. Learning of the non-taxonomic relationships allows implicit reasoning information and infer intra-relation and inter-relation within a given space.

There is a limited number of research studies on the extraction of semantic properties relationship from ontologies. In addition, the existing studies discussed the demand of Natural Language Processing (NLP) based method for the relationship mining process.

In this work, we assume the taxonomic relationships with its individual representation for this proposed approach. Also, this work is utilizing the massive web-scale content to retrieve a context-aware data through a domain-independent manner. It uses a bottom-up approach that utilizes individuals to predicate the non-taxonomic relationships from that pre-processed relevant content that diminish the manual intervention effort. It focusses on the relationship mining and ranking rather than the development of ontologies.

The rest of the paper is organized as follows: Section 2 discusses the related work. Section 3 briefly presents the proposed model with its modules. The empirical results and findings are in section 4. In addition, the conclusion and future work are presented in section 5.

2. RELATED WORKS

Number of researchers have discussed ontology learning approaches and model where the learning non-taxonomic relationships was the least tackled and most challenging [30],[33] [34],[35],[36],[37],[38],[39],[40],[41],[42],[43],[44] ,[45]. A proposed RDF-Deep Neural Network (RDFDNN) for predicting RDF entities' relations on Freebase and WordNet is presented in [44]. In [40], the authors analyze HTML tags in order to deduce relations. The authors [38] studied mining the non-taxonomic relation from domain-specific (smart cities) big data that incorporates semantic graph and context-aware called Semantic Graph-Based Non-Taxonomic Relationships Identification (SGNRI). A semi-automated approach that recommends non-taxonomic relationships through domain-specific corpus computes centroids verbs and verb-vectors representing for relation suggestions presented in [46]. Using models such as the NLP, Finite State Machines (FSM) and comprehensive set of patterns, the research paper [45] proposed a method to discover semantic relation patterns and concepts from Wikipedia. A discovery from a targeted financial corpus of non-taxonomic relationships has been presented in [33]. Another research paper [47] aims to extend the previously built taxonomic hierarchies to suggest relationships from domain-specific text documents. The approach employs existing taxonomic relations and text mining in domain ontologies to come across candidate keywords that can represent semantic relations. Another study tried to determine the clue for semantic labeling is [48]. It suggested techniques using Text-to-Onto, which is a tool based on a corpus of documents, and POS tagging in extracting lexical entities. They indicated that the relationship is usually indicated by a verb relating pair of concepts. The study addresses the problem of the conditional frequency of a couple of concepts and the relation between concepts. Another work enhances the non-taxonomic aspects of the construction of domain ontologies using unsupervised methodology [49]. The study introduced an approach to extract non-taxonomy relationships from the web in number of steps. The research paper addressed the challenge of assessing the semantics triples due to its unsupervised approach. One major difference here is that the principle of dumped data in the proposed work follows an improved model that maximizes relevant contest and minimizes garbage inserting.

The outcome of the review of literature shows that there is a demand for a technique for extracting non – taxonomic relationship. Moreover, the existing methods are limited for a specific domain. Based on the reviewed literature, this work is different because it targets web-scale, domain-independent approaches to mine candidate relationships and efficiently avoid garbage injection. This work focuses on the quality of the inserted data. That is, a bottom-up approach is proposed as an effort to populate non-taxonomic relationships in an efficient and scalable approach.

3. THE ARCHITECURE OF THE PROPOSED APPROACH

This study aims to allocate a suitable relation to a given two individuals entities. That is, based on two given individuals, a collection of directed search pool content is retrieved to create a relevant dump bulk content. That is, context-aware approach is prepared in a domain-independent fashion. That is, a relevant bulk is evolved and generating a corpus based on subjective search. Later, some heuristics are set to explore links

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between individuals. Figure 4 below shows the processes of our proposed approach.

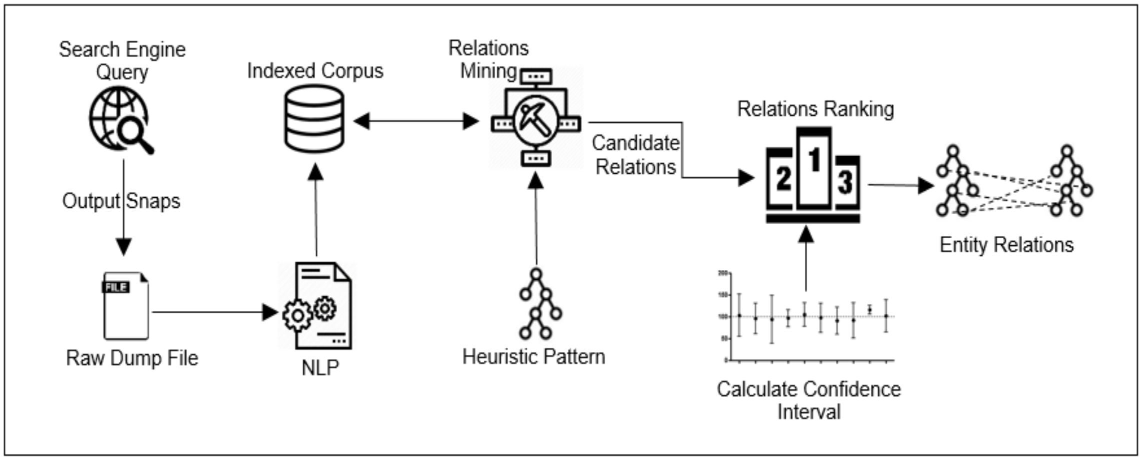

Figure 4: Process Model

3.1 Semantic-Based Bulk Processing

This work proposed efficient and scalable data bulk creation. This initial stage constructs the corpus in a parallel fashion where direct inquiries are injected within dumping the data. This step ensures only related content of the web into local relevant bulk. In this phase of the proposed approach, and based on observation, eight tokens are sets between two given individuals. The tokens are applied and explore the search engine to extract inflations. Then, the initial set of results are stored in a buffer, rFiles. The buffer contains a bulk of phrases that indicate the relations between individuals. The other iteration is set up as search engines adopt number of techniques that assist in retrieving relevant results of a given query. Rather than constructing corpus sole on mining individuals, semantic inputs are incorporated to upsurge a given pair's precision. In order to scale the performance of such a step, a parallel approach is implemented. NLP models have been encompassed for extracting the entities' inflections, filtering hyponyms, stemming, and other tasks. The processes included are getting inflection, which is a term to define a grammatical function or attribute, including tense, person, number, and gender. WordNet 3.0 is used as a search space to identify all hyponyms. The process is presented abstractly below in algorithm 1.

Algorithm 1 Extraction of Phrases
Input: Individual sets
Output: Phrases extracted

```
IN PARALLEL foreach individual in Sets do
    foreach individual * individual in Google do
        rFiles ← store results
        end foreach
    foreach exact relation in Google do
        rFiles ← store results
        end foreach

    end foreach
```

3.2 Relations Mining

This phase is generating all possible combinations. It presents the heuristic set in order to represent an indefinite assumption to improve the decision-making process [50]. To extract a candidate connection in between two entities, the model defined two heuristics. They illustrate verbs that come before the preposition indicates a relation for entities and prepositions, such as "with", "to", "by", "of", "in", "on", "by", and "for". Below, algorithm 2 briefly shows the process. That is, each individual in a set is scanned, and possible relationships are identified using NLP. A phrase score is computed to rank the relations of the individuals. A separate file or buffer storage is implemented for storing the intermediate results and rank the relationship. The proposed relations are then stored in a separate file and processed in

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the ranking procedure.

```
Algorithm 2 Scoring of Relations
Input: Individual sets
Output: Relationship scores
foreach individual in Sets do
    i1, i2 ← extract individuals from Sets
    foreach sn' in rFile do
        oFile ← store extracted relation(R) between i1 and i2 from sn'
        if (i1 R i2) exist then
            updates phrase score in oFile
        else
            add parse in oFile
        end foreach
    end foreach
```

3.3 Relationships Evolution

In order to capture better relations, ranking the results is the key. The confidence interval range of values is derived from sample observations. A search is made to all possible relations among the entities and provides a score for each relation according to the occurrences. A confidence interval is calculated for the top relationships and produced an output. These nominate relationships are then promoted as non-taxonomic relationships to link classes of those associated pairs of individuals.

4. EMPIRICAL ANALYSIS AND FINDINGS

Precision, Recall, and F – measure are the widely applied measures for evaluating the information retrieval system [23]. They compare the effective and expected results of an information retrieval system [24]. Therefore, these measures are adopted for evaluating the proposed method. The experiment process ontologies that include 143 individuals from various domains ontologies including Clothing, Vehicle, and Electronics where individuals of each as following 34, 55, and 54, respectively. The efficacy of information extraction is calculated in the classical Information Retrieval (IR), recall, precision, and F-measurement methods as shown below in formulas (1), (2), and (3). As each word in WordNet has a different meaning in the linguistic expansion approach, it is necessary to calculate these measures to evaluate the proposed architecture's performance.

$$\text{Precison} = \frac{\text{True positive}}{\text{True positive} + \text{false positive}} \tag{1}$$

$$\text{Recall} = \frac{\text{True positive}}{\text{True positive} + \text{false negative}} \tag{2}$$

$$\text{F - measure} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

The overall average precision achieved 83.68%. It is evident that the proposed architecture has obtained an interesting F – measure for three domains. An average F – measure of 83.68% indicates that the proposed architecture can retrieve individuals without difficulties. Below, Table 1 presents the values of Precision, Recall, and F – measure for three different fields of the proposed architecture. Table 2 outlines the Mean, Standard deviation and error for each domain. The outcome of table 2 indicates that the proposed model has maintained its better performance for all domains. In addition, Standard deviation and error represent that the model has covered a maximum part of the dataset.

Table 1 Precision, Recall, F - measure

Domain / metrics	Recall	Precision	F - Measure
Electronics	0.9286	0.7647	0.8387
Clothing	0.8333	0.8824	0.8571
Vehicles	0.7857	0.8462	0.8148
Average	0.8492	0.8311	0.8368

Table 2 Mean, Standard deviation and Error

Domain / metrics	Mean	Standard Deviation	Standard Error
Electronics	0.78	0.42	0.1
Clothing	0.75	0.43	0.11
Vehicles	0.75	0.43	0.1
Average	0.76	0.43	0.1

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A SPARQL query has been configured to examine and candidates retrieved relationships, and a portion of the query results is shown in figure 5.

s	p	o
DVD_Players	come_with	Bags_or_Cases
DVD_Players	supported_by	Phone_Accessories
DVD_Players	connect_to	Audio_or_Video_Conferencing
Desktops_or_All-in-One_Computers	connect_to	Camcorders
Digital_Camera_Accessories	come_with	Phone_Accessories
Digital_Camera_Accessories	come_with	Optical_Drives_or_Storage_Devices
Digital_Camera_Accessories	supported_by	Computer_Cards_or_Components

Figure 5: A portion of the output using SPARQL

In this process, sequential representation of the words in the texts is applied first to WordNet synsets and, according to our model, next to the ontological implications for them. Each synset's implications will be collected by determining the synsets set to which they are connected through hyponymy, which has an ontology map. These ontological forms are then introduced and extended into further impacts arising from the ontological Structure.

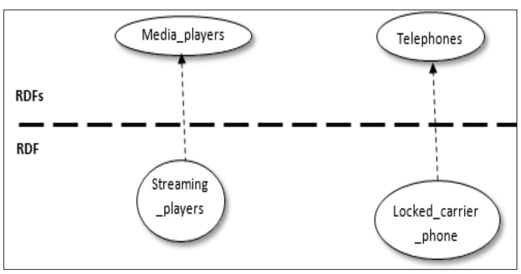

Figure 6A: initial state

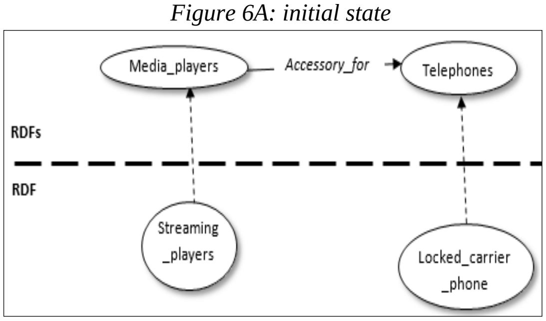

Figure 6B: outcome state

Figures 6A and 6B are an example of the initial and outcome states from the electronics field. The knowledge engineer could enhance the semantic representation using Protégé ontology editing environment and infer the ontological conceptualization, including properties restrictions and axioms, as shown in the elucidation representation in figure 7.

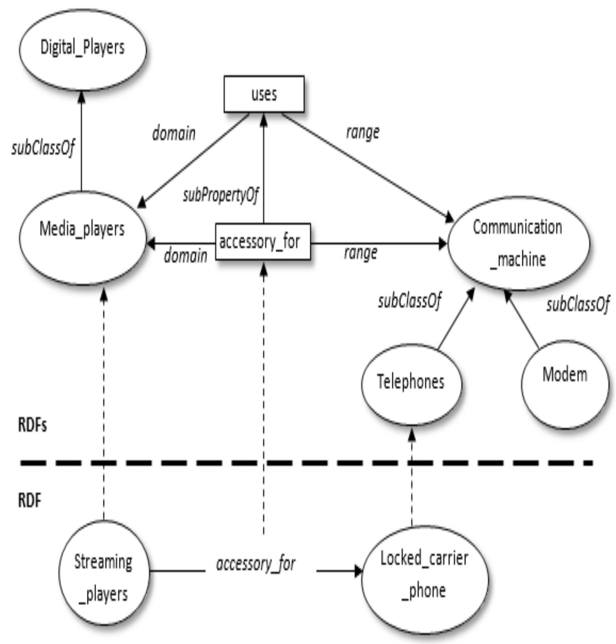

Figure 7: elucidation of semantic nominated representation

Before text mining progression, the preprocessing steps play a vital role, in our case, it included encoding of data into ASCII format, then all HTML characters and URLs are removed from the data. Extracted data are further cleaned by removing some characters like smileys, emojis, expressions, and punctuations. NLP models such as classification, tokenization, stemming, parsing, and semantic wrapping have been set up to enhance the proposed model outcome. The stemming process is used to reduce a word to its root in order to generalize the usage and reduce the process to generate a relation. The intention to apply the stemming process to reduce the dataset's size and minimize the loss of knowledge from the raw data. In the development, the pattern-en, panda, nltk.corpus, NLTK, and Porters Stemmer libraries have been used. Based on the experimental findings, the background information can increase the relationship's efficiency, and, in particular, the best performance can be achieved by integrating different information components with background information.

The study addressed the challenges in semantic properties extraction. The outcome shows that the performance of the proposed method is better comparing to other methods. WordNet contains large number of categories. In this study, three categories were examined for measuring the performance of the extraction technique based on NLP. The proposed method has designed a generalized parsing and pattern matching technique that can be applied in different domains. The proposed study has addressed the research gap in literature of semantic extraction and relationship mining.

5. CONCLUSION

Advance technologies such as RDF and Ontologies promote data to be integrated into a formal and meaningful machine-processable format. Data in this well-formed texture and template can be semantically observed, inferred, and queried. This supports the notation of integrated semantic observation. Also, linking distributed domain-related sources semantically would allow semantic federated querying of data and schema using SPARQL technology. The existing studies provide solutions for specific ontology development. The performance of existing semantic extraction is based on a specific language and pattern matching technique. Thus, identifying non - taxonomic relations is one of the complex tasks in ontology learning. In this work, a novel and generic approach is proposed to extract inflations and links among individuals. That is, a sample of the only related context of the web is processed to mine the non-taxonomic relationships via a bottom-up approach to nominate non-taxonomic relationships. The processed data are injected with relevant pairs extracted via a straightforward procedure. Three domains, including Vehicles, Clothing, and Electronic, were used to measure the proposed approach's efficiency. The proposed method can be applied in other domains. The outcome of the experimentation indicates that the proposed model has achieved promising results. The future work would be focusing on abstractness and concreteness of a given nontaxonomic relationships. Also, assisting ontologies mapping through semantic-based measurements of the nontaxonomic relationships.

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