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ANSWER SET PROGRAM AND STANFORD DEPENDENCY PARSER TOWARD TRANSLATE TEXT TO KNOWLEDGE REPRESENTATION

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ABSTRACT

Knowledge representation is a promising solution that reflects intelligent behavior in artificial systems, so a proposed method is developed in this research which links the Natural Language Processing area with Knowledge Representation area by discussing one possible solution to translate text to knowledge representation. The first step in the proposed method is to get part of speech tagging (PoS) and to extract Stanford Dependency relations for a set of sentences using Stanford parser. Second, a set of linguistic rules will be generated depending on Stanford Dependency relations with PoS to generate knowledge representation for the set of input sentences. The representations reflect deep syntax and grammatical relations between words in sentences. By using theses representations, we can express the structure of the text, and distinguish between the events and their environment in the text. Answer set programming (ASP) is used to implement these linguistic rules. ASP programs consist of rules that are the same as Prolog rules which reflect computational mechanisms that used to create the fast satisfiability solvers for propositional logic, the proposed approach was tested using different metrics and compared with other works using the same dataset, and the obtained results are promising.

Keywords: *Answer Set Programming (ASP), Information Retrieval (IR), Natural Language Processing (NLP), Part of Speech Tagging (PoS), Question Answering (QA)*

1. INTRODUCTION

The proliferation of artificial intelligence concepts relating to voice activated technologies such as bots and chat bots in social media raises the necessity to Natural Language Processing (NLP) which defined as the field that combines computer science and linguistics to handle the natural languages using computers, as NLP can be defined as the set of computational techniques used to present human language. NLP research has developed from analysis of a sentence that took a few minutes at that time to the process of millions of web pages that is now taking a part of second [1]. NLP is characterized by two features, the first feature relates to its similarity to natural spoken language which makes it is easier to understand and write; and second, its automatic powerful translation into a formal language, since formal languages are difficult to understand for domainspecialistandmayresultacognitivedistancetotheapplicationdomains which are not in the core of natural language [2].

NLP is used to enable computer machines to understand and manipulate natural language. Natural language is defined as a set of symbols and rules that govern the relations between these symbols to transfer understandable information between entities using minimization text technologies [3]. NLP can be divided into many subfields such as machine translation, speech recognition, and speech synthesis that are considered important topics in NLP [4]. NLP includes the following research fields: Machine Translation, Information Extraction, Information Retrieval, Natural Language Generation, Natural Language Understanding, Speech Recognition, Summarization, Translating Natural Language Sentence to Formal Sentence in an Appropriate Knowledge Representation Language, and Question Answering [5].

The goal of this research is to translate a text in natural language (called a set of sentences) to knowledge representation in order to be able to use in computer for answering questions in the text. In addition, translating text to knowledge representation can be used by robots, which is emergent trends that are developed to be used in non-conventional solution such as: object detection, activity recognition, machine learning techniques, and artificial intelligence [6].As machine learning is not adequate to be represented alone, and it is better to merge with learning model classifier. So knowledge should encompass all the relative information required by a robot to handle a complex task like knowledge acquisition and reasoning; since building the proper knowledge representation is a challenge, so to solve complex problems, these problems should be divided into sub-problems and assign the proper model for each part, then use large-scale distributed systems and networks to knowledge and experience to teach robots to perform certain tasks from scratch.

One of the most popular theories that designed to represent meaningful representation for different linguistics sciences is Discourse Representation Theory (DRT) that recently arises to handle puzzle semantic problems and semantic problems that deal with tense and aspect [7]. DRT includes interpretation of sentences parts such as: pronouns and temporal expression in the sentence[8].Many researchers have been done to retrieve information and natural language processing by building semantic parser for question answering tasks[9].

The main challenge of translating a set of sentences to knowledge representation is to find the relationship between words in the set of sentences [10], and to find the relationships between words are NP- hard problem because it consists of finding the relationship between a pronoun and its antecedent. The connection between a pronoun and its antecedent is one that has received a great deal of attention in linguistics [10]. In addition, it consists of finding the relations between verb with its subject, and it objects. This research uses Stanford dependency parser to find the relations between verb with its subject, and its objects, and partially finds connection between a pronoun and its antecedent. This research uses dependency grammar representations of sentences Stanford dependency relations using Stanford dependency parser. The representations reflect syntax and grammatical relations between words in sentences. Syntactic (grammatical) representation can express the structure of the text and can distinguish between the actions and their environment in the text. Using a general set of relations between the events and their participants, the same events or entities may be represented in different perspectives. Extracting these features reflects the linguistic rules that are generated for sentences in the text that responds these features then extracting linguistic logic rules for the sentence [11]. The following sections are organized as follows: section two contains the related work, section two contains part of speech tagging, section three contains four Stanford dependencies representations, section five contains answer set program, section six contains the proposed method, and section seven cantinas the conclusion and the future work.

2. RELATED WORK

Since the digital societies are developed recently, there is a crucial need to use different intelligent systems that utilize knowledge representations which are extracted from natural language. This knowledge will be extracted via human users' knowledge or from books, web pages, or documents [12]. Question answering system is a powerful technique that could be used to extract knowledge from those sources. This may be used to automate translation from natural languages into knowledge representation.

In [12], the artificial neural networks were used to automate commands recognition in speech. The success of the proposed system depends on using minimum number of words that contained in the commands to be the input signals to the neural network. This system can recognize more than 85% of the examined words correctly. This value may be increased if the neural network used has more training. In spite of the obvious success in the ideal conditions, the command recognition may be affected strongly by the background noise. The performance of the command recognition is highly sensitive to the background noise which decrease accuracy rapidly depending on the level of the noise. Because of that, the level of background noise must be decreased to the lowest level to improve the ability of command recognition.

Question Answering (QA) is used to represent knowledge, but QA does not give strong Knowledge representation and reasoning and it needs to have idea about the events occur. The main goal of QA is to map data query over a structured database using semantic parsers. Semantic parses usually use predicate calculus or a query language like SQL or SPARQL.

Modern techniques of using QA systems to retrieve the answers of questions using the queries of natural language were proposed. This type of questions retrieval is considered as an advanced type of information retrieval was proposed in literature. It depends on getting a precise answer for each question. Mainly, most studies concentrate on certain aspects of QA. Some of these aspects are domains, hybrid paradigm and information retrieval. The relation between domains, technologies, concepts and metrics were investigated in [13]. The Semantic Web and NLP faced many difficulties in dealing with the QA approaches that are related to the huge amount of data on the web. In open domain environment, the QA systems related to free text could be managed easily. Large amount of data could be managed using Information Retrieval (IR) techniques to get the answer [14] and [15].

In [15], new systematic evaluations have been proposed and the related challenges have been discussed. Also, the question answering over linked data (QALD) challenges have been discussed in details. Moreover, the results that have been achieved via running QALD-1 and QALD-2 were discussed deeply. QALD-1 was discussed firstly in ESWC workshop *Question Answering Over Linked Data* in 2011. While, QALD-2 was firstly discussed in ESWC workshop *Interacting With Linked Data* in 2012.

Another attempt was proposed to extract knowledge from natural language, then to represent the extracted knowledge in proper shape with reasoning it by enrich existing knowledge bases [16]. The proposed framework was developed and implemented using deep analysis techniques that are based on linguistic dependencies. It incorporates the strong obtained results from previous related works, but this work depends on the best parser and how to combine the best aspects of it.

In [16], ranking model dealing with text processing was proposed. This model is a graph depending model and is called Text Rank model. This model is used for applications of natural languages. Two unsupervised approaches were proposed for sentences and keywords extraction. This proposed model is portable for other languages and does not need deep linguistic knowledge. The model depends on building a graph to represent the text and connecting words entities of the text by meaningful relations.

Deep learning methods employ multiple processing layers to learn hierarchical representation of data and have produced state-of-the-art domains. Recently, a variety of model designs and methods have blossomed in the context of NLP. In this paper, a new method is developed toward knowledge representations by using two core features in NLP that reflect deep learning of sentences: PoS tagging for the words in set of sentences and Stanford dependency relations from semantic Stanford dependency parser.

In this research, Part of Speech (PoS) tagging returns list of noun, adjective, and verb that reflects core words in sentences. Stanford dependency relations reflect deep syntax and grammatical relations between tagged words in sentences. Syntactic (grammatical) representation can express the structure of the text and can distinguish between the events and their environment in the text. Many studies have been done to create and build new semantic parser on new domain, one of the studies is to build a parser starting from zero training examples through using a simple grammar to generate logical forms combined with canonical utterances using publications database, then crowd sourcing is used to summarize canonical utterances to natural utterances which is used to train the semantic parse. This study is tested on seven domains

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and the results showed that it can be built in a few hours as it a functionality driven process with exploration of linguistic implications [17].

In [17], the proposed approach has two valued advantages: completeness and supervision ease. The former property was achieved by exercising all grammar rules via generating canonical utterances to gain the completeness which specifies the logical functionality precisely. The later property, supervision ease, is achieved by the paraphrases that represent the source of supervision which just require the question understanding to supervise in contrast to other approaches that require additional step represented by figuring out the answers to the questions. The proposed approach the simple domain-general grammar to reach the point of human understanding of the words and let the human make the necessary corrections to produce the natural language words. This way is used for semantic-parsers building.

There exit some sophisticated problems related to NLP, so deep learning algorithms were proposed to handle Knowledge representation , and most of the scenarios in deep learning research for NLP is supervised learning, but un- fortunately most the real-world scenarios need unsupervised or semi-supervised approach. So, most the learning schemes should be directed on developing deep learning to utilize the use of unlabeled data by developing better models that employ the reinforcement learning methods such as: dialog systems [18]. However, these methods are lacked the finding relationships between verb and its subject, and object from any domain. Also, these approaches are lacking of descriptive representation for the relations between adjectives and its descriptive name. But the proposed method is unsupervised that depends on syntactic structure answer set program rules that discusses one possible solution depending on grammatical relationships between main event (verb) and its parameters, and adjective with its related descriptive name from any domain.

In [18], several models that are designed depending on deep learning are discussed and examined for NLP different tasks and their performance was investigated. The performance for every model was evaluated and compared with the others.

3. PART OF SPEECH TAGGING

PoS Tagging is used to assign a tag to a word, so it is the as the task for assigning suitable PoS tag to each word in a sentence. It can be classified into: open class and closed class. Unsupervised part-of-speech tagging was tackled using hidden Markov models [19].PoS is used as a pre-processing step for language processing activities and tasks, so PoS can be used in text summarization, key phrases extraction, deep parsing of text, text to logic translation. PoS tagging is classified into supervised, semi-supervised and unsupervised tagging. Supervised tagging is based on a pre-tagged corpus to classify words [20], while in semi-supervised tagging a pre-trained neural language models is used to augment token representations in sequence tagging models[21], and in unsupervised tagging, it depends on graph clustering methods, and it does not depend on a pre-tagged corpus [22] & [23]. It generated unsupervised new selective rule-based part of speech (PoS) tagger that concentrates on the most significant parts of speech for translating text to knowledge representation, such as noun, verb, and adjective. Figure 1 shows the usual steps for part of speech tagging system.

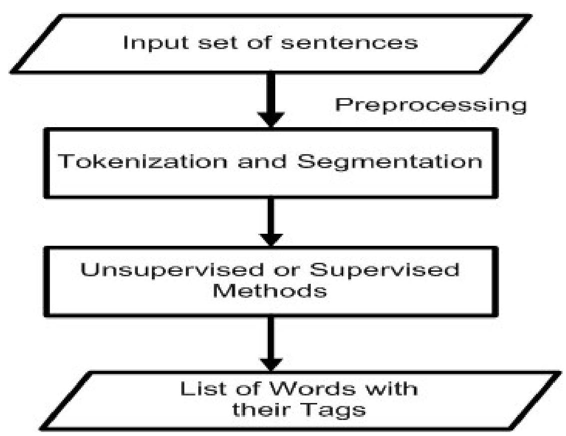

Figure 1: General Steps for PoS Tagging System

4. STANFORD DEPENDENCIES REPRESENTATIONS

In order to simplify the grammatical and structural relationships in sentences, Stanford Dependencies Representations is commonly used, it

provides simple description to sentences which allow people to easily understand and use without the need to be linguistic experts to extract textual relations [24].
Some of the most common relation types and their labels are the following [25]:

- nsubj(nominal subject): A nominal subject is a noun phrase, it is the syntactic subject of a clause; since the relation governor might not always be a verb: the root of the clause is the complement of the copular verb, which can be an adjective or noun if the verb is a copular verb. Example: The boy is naughty. *nsubj(naughty,boy).*
- root: The root grammatical relation refers to the root of the sentence. Example: I like Italian Pizza. *Root (ROOT, like).*
- amod (adjectival modier): An adjectival modier of a Noun Phrase (NP) that serves to modify the meaning of the NP. Example: Ali eats white chocolate. *amod (chocolate,white).*
- dobj (direct object): The direct object of a Verb Phrase (VP) is the noun phrase that is the (accusative) object of the verb. Example: Alaa gave me a hug. *dobj(gave, hug).*
- iobj(indirect object): the indirect object of a VP is the noun phrase which is the (dative)object of the verb. Example: Alaa gave me a hug. *iobj(gave, me).*
- pobj(object of preposition): The object of a preposition is the head of a noun phrase following the preposition, or the adverbs here and there. Example: I sat on the chair. *pobj(on,chair).*

5. ANSWER SET PROGRAM

Answer set programming (ASP) is a type of declarative knowledge and reasoning programming-oriented approach that is directed to solve sophisticated search problems. ASP was emerged in the late 1990s to solve non-monotonic reasoning to represent knowledge; ASP is implemented in several applications including: robotics, bioinformatics and computational biology, some industrial applications, in addition to knowledge representation and reasoning [26]. ASP programs consist of rules same as Prolog rules, but the computational mechanisms used in ASP are different; as they are depending on the ideas that have led to the creation of fast satisfaction solvers for propositional logic [27]&[28]. Also, ASP programmers can manage the computation of stable models via the rules that they include in the logic program.

ASP start working by parsing specific data and transforming these data into internal data structures, then the input variables are eliminated to generate ground program (P) using Instantiated module as depicted in Figure 2. Many ground rules will be generated and adapted to keep the instantiated program which must have the same answer sets. Instaniator optimization and modeling with reasoning are implemented to tackle hard computational algorithms. Search and rewriting based are the main approaches which are used in ASP, in search based approach; backtracking search algorithm is used, while in rewriting based approach propositional formulas are used to find answer set candidates. After finding the answer sets rules, ASP will write the solutions using text format. ASP gets its popularity and spread due to its ability to deal with large complex hard problems within accepted period of time. ASP satisfies artificial intelligence requirement by enhancing the ability of better programming understanding agents through adapting reasoning and undergoing the environmental changes. But, unfortunately ASP address some challenges that are relating to default representation, hybrid reasoning and optimization especially in robotics industrial applications [29].

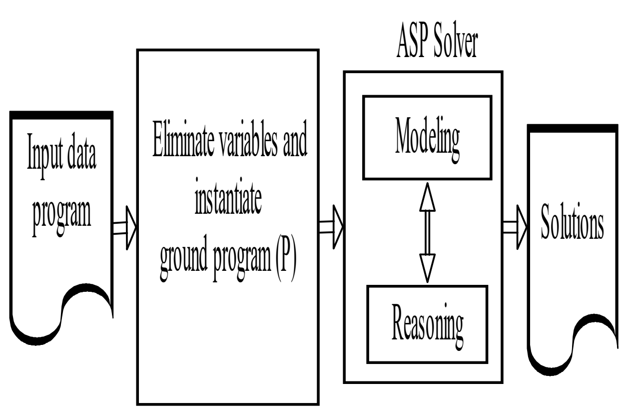

Figure 2: System Architecture of ASP

6. PROPOSED METHOD

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The main idea of this research for the translation from English to a knowledge representation is depend on the identification of the syntactic and grammatical structures of the sentence. The first stage in this research is getting a list of part of speech tagging and Stanford Dependency relations (grammatical and structural relations) for a set of sentences using Stanford parser. In the second stage, a set of linguistic rules will be generated depending on Stanford Dependency relations for the set of input sentences. Figure 3 shows the proposed method.

Extracting knowledge representation for the sentences could be presented by three main parts such: finding the relationship between subject and verb, finding the relationship between adjective and its descriptive name, and finding the relationship between a pronoun and its antecedent.

First, let us discuss how we can find relationship between verb, its subject, and object. Consider the following example: Salma takes the plane (for the sake of simplicity, let us ignore the determiner the). By PoS tagging, each word will be assigned a tag. This research focuses on four main tags: noun, verb, object, and adjective. First, assign each noun, object, and adjective tags of the sentence with unbound variable. For this example, X=salma, and Y= plane. We can begin by stating that lexical items Salam and plane are represented by grammatical and structural relations: nsubj(Salma, takes),and dobj(plane, takes). Next, we need to specify how the verb phrase is encoded from its sub-parts. A possible approach is to represent verb as function that mapping available grammatical relations that hold unbound variables to its parameters. For the previous example, take is function with two parameters X, and Y. Finally, we can decide to encode the sentence by replacing the unbound variable in the function for the verb phrase with the constant, denoting the syntactic subject of the sentence. Hence, we get to take (salma,plane).

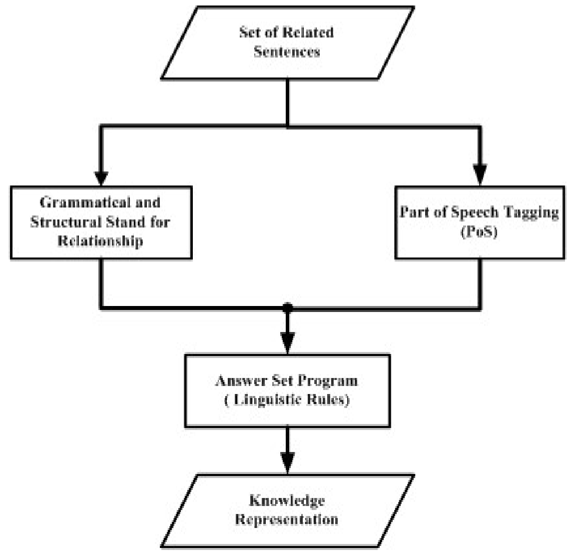

Figure 3: Proposed Method

Second, let us discuss how we find the relationship between adjective and its descriptive name. Consider the following example: Sam eats red meat. Stanford parser returns grammatical amod (red, meat) relationship. From this grammatical relation, the adjectival phrase will be extracted.

Figure 4 shows an example how the proposed method is working. Second, let us discuss how we find the relationship between adjective and its descriptive name. Consider the following example: Sam eats red meat. Stanford parser returns grammatical amod (red, meat) relationship. From this grammatical relation, the adjectival phrase will be extracted as depicted in Figure 5 and Figure 6 respectively.

- some of ASP linguistic rules that are extracted depending on the data set that is collected from[30].
- result of ASP using Clingo that is program which supports ASP declar-ative language. Stanford Dependency relations and PoS tagging for each sentence are extracted.

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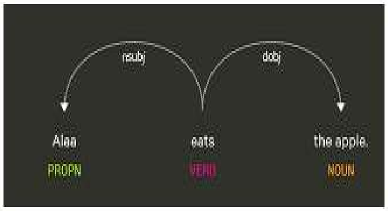
Input: Alaa eats the apple.

NLP Deep learning Processing: PoS tagging and Stanford dependency parser.



ASP linguistic rules:
#const x= alaa.
#const y= apple.
nsubj(eats,alaa).
dobj(eats,apple).
knowladge(Z,(X,Y)):- dobj(Z,Y),nsubj(Z,X).

DRT box knowledge representation :[x=alaa, y=apple , eats (alaa, apple)]

Figure 4: Example explains how the proposed method is working

```
#const x= alaa.
#const y= apple.
nsubj(eats,alaa).
dobj(eats,apple).
knowladge(Z,(X,Y)):- dobj(Z,Y), nsubj(Z,X).
knowladge((Y,(X))):-amod(X,Y).
knowladge(Y,(X)):- nsubj(X,Y), cop(X,Z).
knowladge(X,(M,Y)):- nsubjpass(X,Y), nmod_by(X,M
knowladge(X,(M;Y)):-nsubj(X,Y), cop(X,Z), amod(X
```

```
Solving...
Answer: 1
nsubj(eats,alaa) dobj(eats,apple) knowladge(eats,(alaa,apple))
SATISFIABLE

Models       : 1
Calls        : 1
Time         : 0.007s (Solving: 0.00s 1st Model: 0.00s Unsat: 0.00s)
CPU Time     : 0.000s
```

Figure 5: Snapshot of Some ASP Linguistic Rules and Corresponding Clingo Result

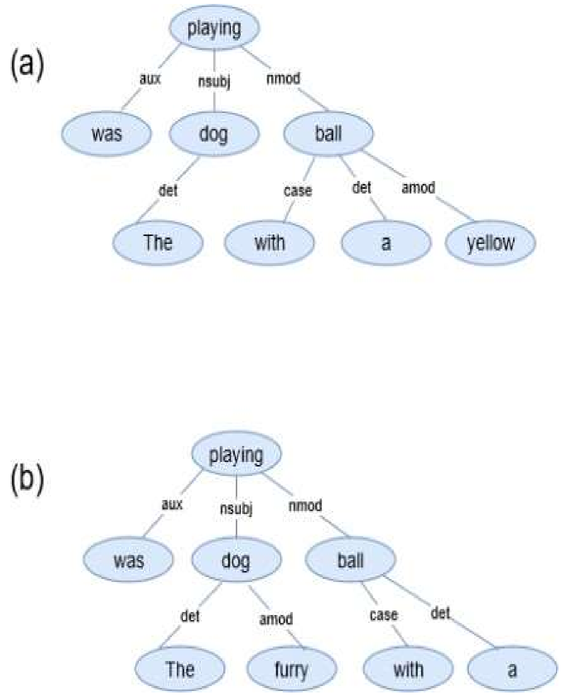


Figure 6: Dependency Trees of The Sentences: (a) The Dog was Playing With a Yellow Ball and (b) The Furry Dog was Playing with a Ball [31].

The main challenge of translating text to the knowledge representation is to find unsupervised translation system that could work with any data set. This research uses a syntactic representation of sentences to generate unsupervised translation system that do not depend training data set but it depends ASP rules that extracted depending on Syntactic (grammatical) representation. Syntactic (grammatical) representation can express the structure of the text and can distinguish between the events and their environment in the text. Using a general set of relations between the events and their participants, the same events or entities may be represented in different perspectives. Keeping these features in mind, a dependency tree is built for each sentence in the text that reflects these features. If sentences that have the same dependency tree, then the sentences have the same Answer set program rules to translate to reflect knowledge representation.

7. RESULTS AND ANALYSIS

In this research the proposed method for set of sentences using Stanford parser, and assigning set of linguistic rules to

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generate knowledge representation for the set of input sentences is evaluated using a set of evaluation parameters including accuracy, recall and Precision [32].

- Accuracy

The accuracy of representing the deep syntax and grammatical relations between words in sentences is important; since it reflects the process of analyzing different types of text used in different applications such as social media tweets and others. However accuracy percentage can be defined as the percentage of correct predictions with respect to the total number of input samples using confusion matrix [33].

$$\text{Accuracy } \% = \frac{\text{TP + TN}}{\text{TP+FN+TN+F}} \text{ x } 100\% \quad (1)$$

Where:

TP represents the true positives predicted samples,
FP represents the negative predicted incorrect samples,
TN represents the negative correct predicted samples, and
FN represents the positive incorrect samples.

- Recall and Precision
Recall and sensitivity are used to measure the true positive predicated samples with respect to the total number of positives predicted samples and negative predicted incorrect samples as shown in equation 2.

$$\text{Recall } \% = \frac{\text{TP}}{\text{TP+F}} \text{ x } 100\% \quad (2)$$

While precision is used to measure the total number of classified samples as true positive samples. Recall and precision can be combined together to produce f-measure score as shown below in equation 3.

$$\text{F} = 2 \text{ x } \frac{\text{Precision x Recall}}{\text{(Precision+Rec }\ )} \text{ x } 100\% \quad (3)$$

F-Score measurement is used to give more evidence about recall and precision as it calculate the average of the mentioned matrices in equation 3. In this research, the performance matrices are tested using the data set composed of 379 sentences that are stored in [34]. The results are shown in Table 1 and Table 2 respectively.

It is clear from the obtained results that the accuracy is acceptable and superior to other researches especially in text structuring and events handling in the text; since NPL is a good solution to remove ambiguity in text classification; since some errors may result from grammars resources library of incorrect mixing between regular and irregular paradigms, and the use of unnatural phrases by native speakers with negative determines.

The results for recall, precision and F-Score is better than other researches a superior with about 5 %, so it is optimistic approach; since it simplifies the understanding classifications of sentences with a high accuracy at a short period of time and understandable manner.

Table1: Accuracy and Precision Results

Metrics	Accuracy %	Precision %
Text Structure	93	88.9
Events and their environment in the text	90	86.8

Table 2: Recall and F-Score Results

Metrics	Recall %	F- Score %
Text Structure	95.8	92.2
events and their environment in the text	95.8	90.9

knowledge extraction from text is a motivation for many researches, in this research we developed dynamic method for transferring natural text to ambiguous and understandable knowledge, the proposed approach will increase the accuracy, and enhance the understanding of machine as it uses the NPL which will enhance the machine readable format; also the proposed approach moves the unstructured ambiguity text transformation to structured approach.

8. CONCLUSIONS AND FUTURE WORK

Knowledge representation is an important topic in several systems, including large-scale distributed systems, networks knowledge sharing and robots training, as these systems will support the coming future generation and intelligence systems. So, there is a complex problem and a sever challenge to build a suitable comprehensive knowledge representation. In this research, answer set programming linguistics rules and an extracted Stanford dependency parser are combined to produce dynamic method for transferring natural text to ambiguous and understandable knowledge. A set of trusted data sets was tested and manipulated using the proposed method; the results showed that the proposed method was unsupervised and easy to understand, in addition to their superiority compared to other works. We plan to develop a standards and a matrix that is used to measure knowledge representation to adapt accurate systems that will assist in developing the realm of service robotics for safe and reliable robots to be deployed amongst humans, and to study wider data sets using different parser tools. In addition, to hit another point in knowledge representation is to find the relationship between a pronoun and its antecedent by using different parser such Turbo somatic parser that fined the type of these relations. Finally, we plan to extend our researches on larger dataset using different parser, and use the extracted dataset to develop an artificial learning models like neural networks.

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