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Literature Survey in Natural Language Processing In the Sphere of Relation Extraction

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ABSTRACT
Today data is being produced at a phenomenal rate since our ability to store the data has been grown. Most of this available data is in unstructured form. Information extraction aims to extract structured information from the kinds of unstructured textual data and is considered as pre-processing step for relation extraction. Relation Extraction is a technique used for exploring the significant relations that would be useful for information retrieval, question answering and summarization. This paper discusses various methods for extracting different relations from the text and provides a consolidated literature survey giving complete idea about the most renowned methods of Information Extraction in Relation Extraction field. It tries to explain the methodology of the mostly used methods of Relation Extraction along with their pros and cons. It proves as a basic study for further exploration in the field of Relation Extraction.

KEYWORDS: *Data mining, Information extraction, Relation extraction.*

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I. INTRODUCTION

Information extraction is a technique used for fetching relevant data. It deals with Named entity recognition, Co-referent noun phrases, Semantic roles, Relation extraction, Time line recognition.Named entity recognition is based on detection and classification of expressions, which refers to specific person, place, etc.Co-referent noun phrases extraction uses different expressions for the same person or object. E.g. the pronouns he or she that refer to the person mentioned before in the text.Semantic roles are assigned to syntactic parts of sentence. They represent actions, states, participants or consequences.Relation extraction is focused on finding relations among already recognised entities.Time line recognition detects absolute temporal expression like concrete dates or times and relative temporal expressions like yesterday, tomorrow etc and it also detects the timeline containing already found events.Normally, relations between entities, such as person, organization, and location are subject of interest. Examples of relations are person-affiliation and organization-location. A relation is defined in the form of a tuple $t = (e_1, e_2, ..., e_n)$ where the e_i are entities in a predefined relation r within document D. Most relation extraction systems focus on extracting binary relations.In the following section we are going to explain various methods of relation extraction namely Large-scale relation extraction (RE) system using distant supervision[1],supervised method for the detection and extraction of Causal Relations from open domain text[2], ternary biological relation extraction[3], Biological event extraction system[4], Unsupervised relation extraction system[5],Vector space model for social relation extraction[6],Positive only relation extraction PORE[7],Ontology driven relation extraction system[8], Co-learning method for relation extraction[9], Snowball System[10], Machine learning method using maximum entropy model[11], Association mining method[12].

II. EXPERIMENTAL DETAILS

Large-scale relation extraction (RE) system using distant supervision [1] learned grammar-based RE rules from the Web by utilizing large number of relation instances as seed, thus covering the actual range of linguistic variation. The system was used to detect both binary and n-ary relations. Distant supervision is considered to be an important technique for data driven RE (e.g. [13, 14, 15, 16]) because of the availability of large knowledge bases such as Yago [17] and Freebase. It utilized a large number of known facts of a target domain for automatically labelling mentions of these facts in an unannotated text corpus, hence generating training data. This was a large-scale RE system that employed Freebase facts as seed knowledge. The obtained rules were then applied for the extraction of new instances from new texts. A rule-filtering scheme that exploited negative evidence obtained from the applicability of a rule to other relations of the same essential type was deployed thereby increasing the precision. This system further also accommodated n-ary relations. This was the first approach to RE which learned large-scale grammar-based RE rules for n-ary relations from the Web in an efficient way. Fig1 explains the workflow of this system.

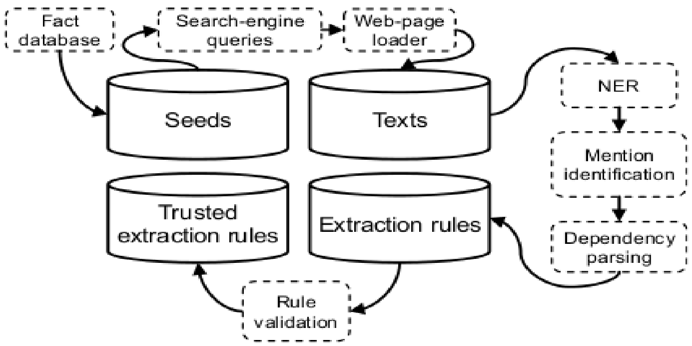

Fig1: Workflow of the large scale relation extraction system

Eduardo Blanco, Nuria Castell and Dan Moldovan [2] presented a supervised method for the detection and extraction of Causal Relations from open domain text. It only considered marked and explicit causations.
A detailed knowledge of what can be considered as causation and its formal definition can be found in [18]. This approach first identified the syntactic patterns that may encode a causation and then used Machine Learning techniques to decide whether or not a pattern instance encodes a causation. It focused on the most productive pattern, a verb phrase followed by a relater and a clause, and its reverse version, a relater followed by a clause and a verb phrase. As relaters it considered the words as, after, because and since. For detecting Causal Relations, some distinctions were used like Marked or unmarked, Ambiguity, Explicit or implicit. Following table shows the features that are used for discriminating between cause and ¬cause. It added a new feature, lexical clue, which allowed to discard some mismatches.

Feature	**Rationale**	**Examples**
Relator	A relator can encode a causation always or sometimes	- [*cause*] *"Leadership is lacking in our society* ***because*** *it has no legitimate place to develop."* - [*¬cause*] *"We had met two years* ***after*** *she had arrived."* - [*cause*] *"Marty stood for several moments with his mouth hanging open foolishly* ***after*** *it had happened."*
Relator left and right Modifiers	causations can hardly be signaled by a *relator* modified by some POS tags	- *adverb* + *after* almost always signals a temporal relation, not a causation: *"This was* ***long after*** *Morse had left the house."* - *as* + *preposition* can hardly signal a causation: *"... he felt he was noting it,* ***as if*** *it were ..."*
Semantic Class Cause Verb	only certain verb senses can express a cause	- if the relator is *after* and the cause verb semantic class is *be-v-3*, then it is a temporal relation, not a causation: *"We heard him yelling after he was out of sight."*
Cause Verb is Potentially Causal	if a verb sense is potencially causal, then is more likely to express a cause	- *ring-v-1* is subsumed by *sound-v-2*, which gloss is "*cause to sound*"
Semantic Class Effect Verb	only certain verbs can express an effect	- If the relator is *after* and the effect verb semantic class is *express-v-2*, then is not a causation: *"My name's Gisele", the blonde said after she ordered a Scotch".*
Effect Verb is Potentially Causal	if a verb sense is potencially causal, then is more likely to express an effect	- *walk-v-3* is subsumed by *travel-v-1*, which gloss is "change location"
Verb Tense Cause and Effect Verb	depending on the relator, some verb tenses are not likely to express causation	- If the relator is *as* or *after*, the cause verb is present and it is not a copula, then is not a causation: [*¬cause*]: *"Henrietta was discovering, as the born writer does, not merely ..."*; [*¬cause*]: *"To play the guitar as he aspires will devour his ..."* - If the relator is *as* and the effect verb is conditional, then is not a causation: *"She wouldn't go as Maude suggested."* - If the effect verb is progressive, then is not a causation: *"The burden of his secret was pressing down on him, as it was on them."* - If the effect verb es passive, then it is more likely to express a causation: *"... and then Richard was shocked as, all at once, flames shot out from the sharp features of ..."*

Table 1: Features considered for the Machine Learning approach

The method described in [3] explored ternary biological relations like PROTEIN-ORGANISM-LOCATION (POL). It used a much larger set of syntactic features extracted from parse trees, many of which were found to be useful in Semantic Role Labelling (SRL) task. It combined a linear kernel with a tree kernel for improved performance. It splitted the POL ternary relation into binary relations like PROTEIN and ORGANISM (PO), and PROTEIN and LOCATION (PL).The PROTEIN name was taken as the predicate (verb) and the ORGANISM/LOCATION name as its argument candidates in question. Then binary SVM classifier was trained for extracting the binary relations. PL and PO binary relations belonging to the same sentence and having the same PROTEIN NE were fused for the prediction of ternary relations. The prediction was made by the sum of confidence scores (produced by the SVM) of the PL and PO relations. Fig2 explains the workflow of this system. This system explored the use of rich syntactic features for the relation extraction task. A large number of features originally proposed for the Semantic Role Labelling task were used by this system. Upto 71.8% accuracy was achieved using rich syntactic features obtained by combining SRL features with tree kernels over the entire tree.

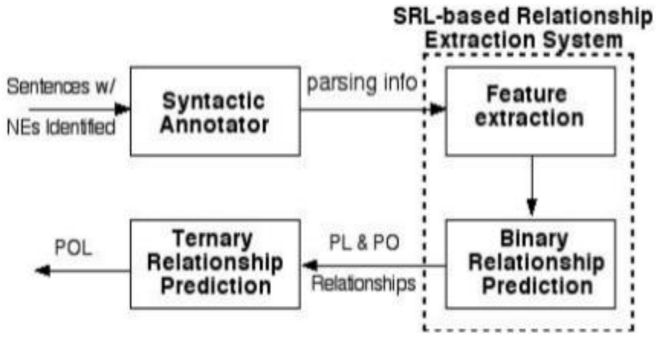

Fig2: Workflow of the system to extract ternary biological relations

Recently, in the biological domain the research focused towards the extraction of detailed and expressive representation of biological information. One such method is the biological event extraction method proposed by Aymen Elkhlifi, Maha Amami and Rim Faiz [4] that referred to the task of detection of typed, text bound events and assignment of proteins as arguments, using basic tools for biological and biomedical text analysis and manually event annotated corpora[19]. The biological event extraction template was defined by a trigger and arguments [20].The semantic roles were assigned to these arguments.Most of the event extraction systems were pipelines of three sub-tasks [21]. First is *Pre-processing* that provides syntactic and semantic analysis of texts as an input to the event detector modules, second is *Trigger detection* that requires assignment of each token to an event class and the last one is *Argument detection* that consists of finding all participants in an event and assigning the functional role to each of the determined participants in an event.

In supervised learning methods, the biggest problem was a great deal of time and efforts were required to prepare annotated corpora, large enough to give efficiency. The varieties of relations obtained from this method were also limited. In weakly supervised learning methods, initial instances or seeds were required, E.g. [5]. The lack of clarity about how initial seeds should be selected and how many seeds are required makes this method a little inefficient. Another drawback was that this method was limited to functional relations only.

To overcome the drawback of these two methods Takaaki Hasegawa, Satoshi Sekine and Ralp Grishman[5],proposed a new approach called unsupervised learning method. The key idea was to cluster pairs of named entities according to the similarity of context words intervening between them. This method only required a NE (Named entity) tagger. The process included Steps like

[1] Tagging named entities in text corpora
[2] Getting co-occurrence pairs of named entities and their context
[3] Measuring context similarities among pairs of named entities
[4] Making clusters of pairs of named entities
[5] Labelling each cluster of pairs of named entities

As discussed in [6], Social network analysis (SNA) is significantly about research of social relations as well as structure in social environment. All the dependencies between people, organizations and environment constitute one or several networks. The author [6] presented a vector space model (VSM) approach to extract and represent relations from text corpus. His paper [6] utilized VSM and implemented a social relation extraction method for text corpus. The approach presented the relationships between cases and affiliations with an incidence matrix. After candidate relations were computed quantitatively, the incidence matrix was decomposed into case-by-case matrix and affiliation-by-affiliation matrix.

Extracted relations were divided into strong interactions and weak interactions according to values of matrix elements. This approach was applied to the text corpus, involving social relation and structure information and used formal language, which could be news stories, intelligence data, business information, etc.
Another method called PORE (Positive only Relation Extraction) [7] for extracting relations from Wikipedia pages was described by an author Miriam Käshammer. It dealt with finding semantic relation existing between a Wikipedia page p and a related page p' which is linked on page p, and other relations like relation between different entities on a Wikipedia page by using info box as a reference for possible relations. It used the structure of Wikipedia articles to semi-automatically extract semantic relations from free Wikipedia text. The steps

proposed for POL algorithm are as follows:
[1] Extract entity features from semi-structured data of Wikipedia.
[2] Extract context features from the co-occurrence of two entities in one sentence in The Wikipedia text.
[3] For each relation, filter out irrelevant pairs.
[4] Conduct relation classification on the filtered set of pairs using B-POL.

There is another method [8] which described an ontology-driven system used for performing relation extraction over textual data. The system exploited expert knowledge of the domain, including lexical resources, in the form of ontology to drive the extraction of patterns using manually annotated texts. Such patterns were then applied in order to identify candidates for relation extraction. Paired with basic, reliable named-entity-level text annotation, it resulted in the discovery of relations among entities in Italian newspaper articles .The authors [8], presented a fully implemented NLP tool for the Italian language called Redada, which used prior knowledge coded by ontology. They presented the context application domain, by describing the ontology creation process. They described how the ontology drives the relation extraction process based on patterns, and how they generate those patterns in a semi-automatic way. The first results looked very promising with about 80% of precision of the relations extracted.

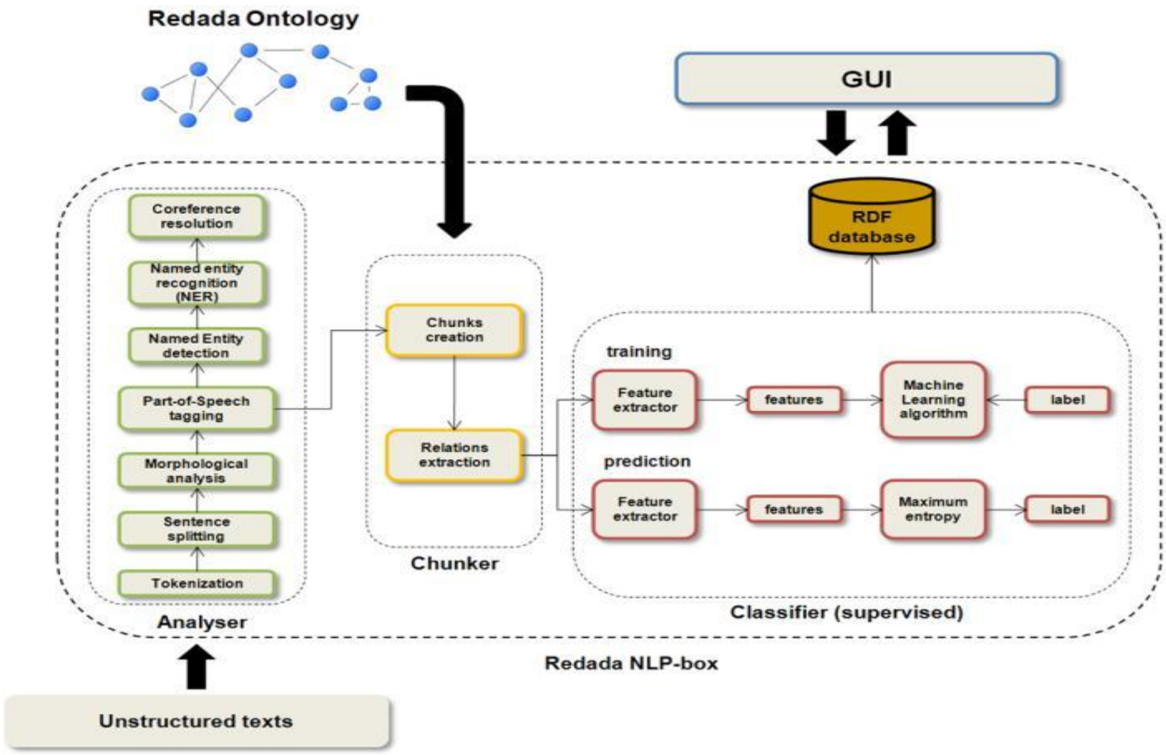

Fig 4: Ontology driven relation extraction.

It may be possible that different relations may be present between two same entities. Thus, A.Cvitas[9] proposed a co-learning method to expand labelled sets of objects with unlabeled ones and improve the quality of information extraction. The basic idea was to use the redundancy of unclassified data or in other words, to view the same data from different angles. These different angles could be used using distinct features like lexical and syntactic features.Co-learning was implemented using two or more classifiers, which learned based on the same smaller set of examples, but disjunctive feature sets.

Features should be divided independently as the sets. In each iteration classifiers worked with the same set of classified examples and those they agreed about with highest certainty were added to chosen class. Those examples were added to the classified learning set and the whole procedure was repeated until the satisfying level of accuracy was obtained.Data is best exploited if available as a relational table that we could use for answering precise queries or for running data mining tasks. Therefore Eugene Agichtein and Luis Gravano built Snowball system [10]. Snowball introduced novel strategies for generating patterns and extracting tuples from plain-text documents. At each iteration of the extraction process, Snowball evaluated the quality of these patterns and tuples without human intervention, and kept only the most

reliable ones for the next iteration. Snowball used basic model of DIPRE[22] for extracting patterns and tuples.

[1] Initially, DIPRE was provided with a handful of instances of valid pairs.
[2] A general regular expression that the entities must match was also provided by the users.
[3] DIPRE examined the text that surrounded the initial tuples and generated a number of patterns from initial seed tuples.
[4] DIPRE scanned the available documents in search of segments of text that would match the patterns.
[5] The new tuples generated by DIPRE were used as new “seed” and the process continued.

Snowball introduced a strategy for evaluating the quality of the patterns and the tuples that were generated in each iteration of the extraction process. Snowball patterns were weighed based on their selectivity. Thus, a pattern that was not selective had a low weight. The tuples generated by such a pattern would be discarded, unless they were supported by selective patterns. Thus tuples with high confidence and that were “sufficiently reliable” only were kept.Lin Yao,Cheng-Jie Sun, Xiao-Long Wang, Xuan Wang [11] had proposed a machine learning method based on maximum entropy model for extracting relations like protein-protein interaction [23-27], Gene-disease interaction [28-30] and Disease-treatment interaction[31].It mainly focused on Disease-treatment and considered relations describing a wide variety of conditions and defined the candidate semantic relationships in one sentence as following 7 categories *Cure*: The treatment cures the disease. *Only DIS*: The treatments are not mentioned. *Only Treatment:* The diseases are not mentioned. *Prevent*: The treatment can prevents the happening of disease.*Vague*: The relationship between disease and treatment is not clear. *Side Effect:* the disease is the side effect of treatment. *No cure*: The treatment cannot cure the disease. He used the MeSH thesaurus for his system.

Use of association rules for data mining made relation extraction easier. *Association Rules* are the statements that find the relationship between data in any database. Association rule has two parts “Antecedent” and “Consequent”. For E.g. {egg} => {milk}. Here egg is the antecedent and milk is the consequent. Criteria like “Support” and “Confidence” are used by association rule for extracting important

relationships that are explained below:

An indication of how frequently an item occurs in database is known as *Support* (s). For a rule A=> B, its support is the percentage of transaction in database that contain AUB (means both A and B).
Confidence (c) indicates the no of times the statements found to be true. Confidence of the rule given above is the percentage of transaction in database containing A that also contain B. One of the algorithms used for association rule mining is Apriori algorithm. Apriori Algorithm [12] is the most famous and classical algorithm for mining frequent patterns which uses bottom up strategy. It was first introduced by R.Agrawal. It uses prior knowledge of frequent item set properties. It employs an iterative approach known as a level-wise search, where k-item sets are used to explore (k + 1)-item sets. First the database is scanned to accumulate frequent 1-item sets and their respective counts. Then only those item sets are collected that satisfy minimum support. This set is used to find frequent 2-item sets, which is further used to find frequent 3-item sets and so on until no more frequent k-item sets can be found. To improve the efficiency of level-wise generation of frequent item sets, Apriori property is used. *Apriori property* states that all nonempty subsets of a frequent item set must also be frequent. Thus at each step non-frequent item sets are pruned making the algorithm more efficient.

III. RESULTS AND DISCUSSION

The table below summarizes all the methods described in detail above :

Sr. No.	Name of method	Type	Description	Advantage	Limitations
1	Large-Scale Learning of Relation-Extraction Rules with Distant Supervision from the Web	Supervised	It uses distant supervision. Uses known facts from web that are stored in Freebase. Used for extracting n-ary relations.	As web is used large amount of linguistic variation is covered. First approach for n-ary relations.	Requires richly annotated data, hence great deal of time and effort.
2	Causal Relation Extraction	Supervised	Uses distinctions like marked and unmarked, ambiguity, Explicit and implicit for classifying the causal relations. Uses features like relater, left and right modifiers, class cause and effect verbs etc to discriminate between cause and -cause.	Relatively simple but yields high performance and adds a new feature called lexical clue to existing features.	Error exists due to inability to discriminate between cause and -cause when causation is signalled by as or after
3	Exploiting Rich Syntactic Information for Relation Extraction from Biomedical Articles	Supervised	Used for ternary relations like protein-organism-location. Extracts binary relations using SVM and then fuses them to form ternary relation. Uses Semantic Role Labelling.	Using rich syntactic features by combining SRL features with tree kernels over the entire tree obtains 71.8% accuracy.	More suitable for data from specific domain and ternary relation extraction only.
4	Biological Event Extraction	Supervised	It includes steps like syntactic analysis, semantic analysis, and uses kernel method functions for trigger detection and argument detection	Useful for finding complex relations from biological literature.	Efficiency depends on the kernel based method function used.
5	Discovering Relations among Named Entities from Large Corpora	Unsupervised	Cluster pairs of named entities depending upon the context words intervening between them.	No need of highly annotated data and initial seeds. Automatically discover new relations from the text	Suffers from semantic drift and performance depends on corpus data properties and not on trustworthy data.
6	Vector Space model for social relation extraction.	Unsupervised	Extracts relationships between cases and affiliations with an incidence matrix. The incidence matrix was decomposed into case-by-case matrix and affiliation-by- affiliation matrix.	Provides an efficient way for extracting and formalizing social network relations	Uses data from various domains resulting into too large matrix.
7	PORE-Positive Only Relation extraction	Unsupervised	It finds the entity features and context features from info box given in the Wikipedia page and filter out only the positive instances from them and finds the different relations existing in that page	A good approach to find semantic relations between two Wikipedia pages or between two entities in a Wikipedia page.	Applicable to web pages only.
8	Ontology driven relation extraction using pattern matching	Supervised	A fully implemented NLP tool for the Italian language called Redada, which use prior knowledge coded by ontology. It is a relation extraction method based on patterns which are generated in semi automatic way	It gives approximately 80 % precision.	Uses tool Redada which is specific to Italian language only.
9	Relation extraction using co-learning	Semi-supervised	An attempt to expand labelled sets of objects with unlabeled ones. Views the same data from different angles using lexical and syntactic features.	Very useful for entity pairs with multiple relation types.	When the unlabeled data is huge compared to the labelled data , leads to degradation in the accuracy as compared to learning only from the labelled data.

10	Snowball: Extracting Relations from Large Plain-Text Collections	Semi-supervised	A strategy for evaluating the quality of the patterns and the tuples that are generated in each iteration of the extraction process.	It gives sufficiently reliable patterns and requires only a handful of examples for training. Gives high precision compared to other models.	The extraction patterns in Snowball are mainly based on strict keyword-matching. Thus recall will be limited. Snowball does not have an elegant evaluation measure, such as the probability/likelihood of a probabilistic model, to evaluate generated patterns.
11.	Relationship Extraction From Biomedical Literature Using Maximum Entropy Based On Rich Features	Supervised	A machine learning method based on maximum entropy model to address the multiple Disease-treatment interaction relationship extraction problems are used. It uses MeSH thesaurus.	Simple and effective method. There is no need of lexicons.	The method highly depends on the labelled data. The contribution of different features should be considered and needs to be explored.

IV. CONCLUSION

From above discussion it is inferred that many methods have been proposed to extract relations between different entities from textual data. The above literature review covers a wide variety of methodologies for relation extraction all of which fall in one of the three categories viz. Supervised, Semi-supervised and Weakly Supervised. Supervised method requires highly annotated data, while in Weekly supervised method only initial seeds (examples) are required. This method depends upon data properties and thus has performance drift. Semi-supervised is a combination of above two methods. The precision and recall of these methods vary from relation to relation which is getting extracted.

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