Named Entity Recognition (NER) in NLP Techniques, Tools Accuracy and Performance

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Abstract

A huge amount of textual information is available on Web, Facebook, blogs and Wikipedia, everyday rising new techniques, algorithms and tools extract the useful information. Therefore, Named Entity Recognition (NER) is a very important technique to recognize the noun entities such as names, date or time, location, medicine names etc. Many researchers have proposed many techniques in different languages and domains for extracting information from text that techniques help to develop new NER applications. Here, we discuss NER techniques: rule-based, learning-based and hybrid approaches and their application and systems. We also present advantages and disadvantages of different libraries and their tools using Java, Python, and Cython programming languages which are SpaCy, Apache OpenNLP, StanfordNLP and tensorflow. Few libraries serve the NER pre-built models that we use for comparison. We compare these few libraries based on training accuracy, model size, time prediction, training loss data and F-measure. The data set is the same for all libraries during training and testing, Spacy library provided a higher performance accuracy and good results as compared to the other models.

Keywords: Named Entity Recognition, Rule-based approaches, hybrid approaches, NER Supervised Learning, Unsupervised Learning in NER

Introduction

Nowadays, a large amount of digital form data (such as email, social applications, newspapers and Instagram) is available in different languages. This information is collected in structured and unstructured form to process the data for extracting useful information but it is the biggest challenge to extract meaningful knowledge such as big data. The main focus of NLP is to get useful information of the human local and information languages so that machines can better perform after

understanding human languages information [1]. NLP many information extraction systems are developed that process question answering [2] and summarize text automatically by using machines well explained by [3].
NER plays a vital role to get semantic information, words, relationships and meaningful entities from text. Past NER research models take input in different forms and identity specific entities [4].

By taking in the view the use of NLP we cannot neglect the practical implementation of the NER in various text formats of different languages. The task dependent specification of the NLP is getting more important and the NER is already a special purpose; it does not work on general problems like the medical one [6]. Where the patient name, disease and medicine name are the important information that must be extracted using the NER. On the other end, one more implementation of the NLP in the Commerce field where the data is important on the bases of product name, customer name, stakeholders, etc.

Named Entity Recognition (NER) is the task to identify named entities like person names, organizations, time, locations, etc. from a given data set or corpus. Named entities also include other entities like medical domain entities, food entities and user also defined named entities in corpus. For instance:

Text

Jhon bought 500 shares of Acme Corp. in 2016.

Output

Jhon **[Person]** bought 500 shares of Acme Corp **[Organization]**. in 2016 **[Time].**

Named Entity Recognition (NER) Techniques

There are three main techniques for NER names: rule-based approaches, learning-based approaches and hybrid approaches.

Rule-based NER approaches

Rule-based approaches consist of the set of rules which are hand-crafted by experts. The rules are based on syntactic-lexical patterns, linguistic and domain related knowledge [5]. Rule-based Named Entity Recognition and Classification systems are worked on domain specific features for obtaining the sufficient accuracy and highly efficiency. Although these systems have some limitations that are costly, non-portable and also domain-specific. Moreover, these systems need human expertise for the knowledge of the domain with programming skills. These systems do not transfer across domains. Besides , Rule-based NER systems developed only for one domain are not portable into other domains.

1.1 Learning-based NER approaches

Machine learning concerns automatically learning with complex patterns and algorithms which makes these system decisions more efficient. Learning-based approaches are splitted into three categories:

- Supervised Learning NER approaches
- Semi-Supervised Learning NER approaches
- Unsupervised Learning NER approaches

2.2.1 Supervised Learning NER approaches

Supervised learning techniques are based to train machines by using a labeled training data set or corpus and predict outcomes for unseen data sets or corpus. Suitable features selection or label collection is a significant task in supervised learning based NER systems. Labels play a vital role to generate learning modals. These models are capable of recognizing patterns and classifying data sets correctly. The selection of the learning algorithm is also important for NER systems. Different researchers use several learning techniques for Named Entity Recognition (NER) Systems. For instance: Hidden Markov Model (HMM) NER based systems, Support Vector Machine (SVM) NER based systems, Maximum Entropy Markov Model NER based systems etc[6].

2.2.2 Semi-supervised learning approaches

Semi-supervised learning approaches use a small amount of labeled data (are called seed) then combine it with a large amount of unlabeled data or corpus. For Example: you have a date set of some photos of different animals. Some data is labeled by name such as (cat, dog, cow etc.) but most of the data is unlabeled so that you can apply supervised and unsupervised techniques to make best predictions for unlabeled data or corpus. The semi-supervised learning “bootstrapping” method that is used for named entity recognition (NER).

2.2.3 Unsupervised Learning NER approaches

Unsupervised learning algorithms use information which is not classified or labeled. These Unsupervised Learning approaches purely apply into unlabeled data for decision making. The main two unsupervised learning approaches are: clustering and association. Clustering based approaches use distributional statistics to find out name entities on the basis of context similarity. Association rules technique apply where you want to find name entities or rules within a large data set or corpus. Unsupervised Clustering applies into different languages for Named Entity Recognition (NER) explained by [3].

1.2 Hybrid NER approaches

These approaches are a combination of best rules of both Machine learning (such as learning-based) and rule-based (Human expertise) techniques. Different researchers introduced many hybrid Named Entity Recognition models. Hybrid systems are more accurate and flexible as compared to other individual systems which use a single learning approach [7].

2 Different Types of NER Methods Overview

Table 1. Description or summary placed above the table.

Paper author name and reference	**Description or summary**
H. Sintayehu [8]	This paper compares the two Semi-supervised approaches LP and EM which are used for NER. LP is a semi-supervised graph-based algorithm where node represents labeled or unlabeled and when one node is tagged it moves into unlabeled nodes, the transaction of nodes depends upon edge weights. EM is also another semi-supervised learning algorithm which assigns tags of words by probability and one factor used to retrain the model; this factor provided predicted label against each word. LP is generated by a new data set.
Popovski,G. [9]	In this paper author proposed FoodIE method which consist on semantic information about food recipe names and fellow rules-based approach (see Fig. 1) for fellow Foodie methodology. FoodIE basically consists of four steps, first step is Food-Related pre-processing in which Quotation marks are removed from the raw text, every sequence of white spaces converted into single space and then all frictions converted into real numbers. POS-tagging in text and post-processing of the label set done in a few second steps by using the UCREL and Core NLP. After that, in the third step semantic tagging of food tokens is done by using the Boolean expression which is ((C1 OR C2) AND C3), if the result of expression is true then it tags as food token. In the fourth and last step food named entity recognition is done with every single food entity which has already been extracted from the food corpus.

Furrer[10]	This paper proposed a new data mining hybrid tool (OGER++) which is used for extracting biomedical entities and linking of words. OGER++ is a combination of dictionary-based entries and text disambiguation entries. Dictionary based entries use the strategy look-up for spelling checking and the NN approach is the post filter of the first one. This system has four major steps (1) text parsing shape (2) normalization (3) disambiguation entries (4) serialization. Step1 used plain text format and XML and JSON used for parsing. Step2: find the biomedical entities and link them. Step3 span each normalized text, then post-filter predicts all entities except tags or labels entities by using probability distribution and consider highest probability of words, if the highest probability is less the control parameter than the second highest entity and remove entity is not entered in labels. Step 4 Once the entity is assigned in the label it does not include again for annotation.
Śniegula[11]	The basic objective of this research is to compare the most commonly used NER tools i.e. CRF and LSTM for the performance purpose that how can they detect large numbers (34) uneven frequency within the NER. Checking the UMLS MetaThesaurus Coordination with CRF to enhance the performance of NER. 8 tests are performed on the corpus. While comparing the values they have extended their comparison by using existing tools with less user effort on the bases of open source libraries presented in different programming languages. The purpose of most of the libraries is to extract information like person, location, organization names. One of the libraries is Stanford Named Entity. The CRF algorithm as a plug-in is available in different languages while written in JAVA. Some more recognized NER tools available like spaCy in python that is second best in the list.
Jiang [12]	Well formulated library is Stanford library that is better in performance and processing Speed but there is no detail mentioned in documentation about the model implemented in the background. The main purpose of the comparison is to drag out something that works best in the clinical that why consider the CliNER open-source library. The author of the library claims that they achieved 0.83 F1[12] with NER from the data. This library includes all the methods that are required for the medical studies, and extracts words like “Treatment”, “Test”,`` Problem".
Boang [13]	Three tests are made in the first test CRF is implemented along with the CliNER CRF classifier. While in the second test the CRF is implemented with UMLS MetaThesaurus. In the third test the LSTM is implemented with the CliNER and the word level Bi-LSTM while the LSTM is totally based on the Keras Python deep learning library well explain in.

	CRF achieves a micro F1 score over 4% better than the alphabetic split while the LSTM achieves 7% better results. While using 70/30 split in combination with UMLS the CRF achieve a score of F1 57.53% on micro while the macro F1 score is 40.08%. When it comes to the entity occurrence on 600 time the F1 score of CRF is 70% and LSTM also achieve a score of F1 70% It is been seen that the results of falloff -3.55% for DNA class at the same the RNA results are increased by the 11.15%

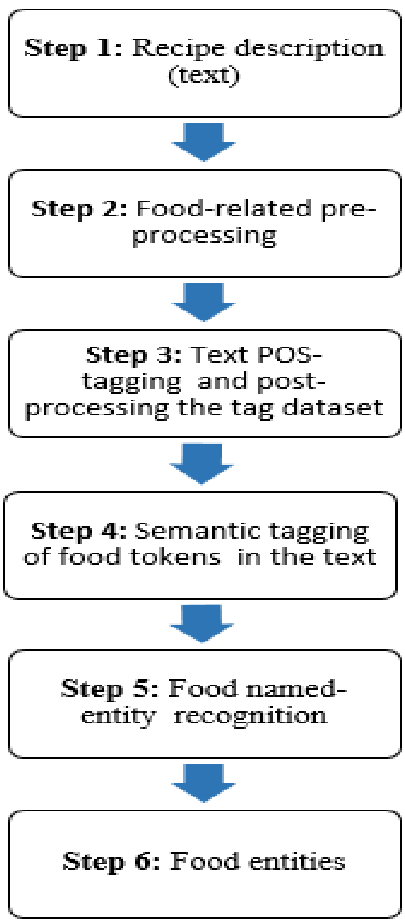

Fig 1: FoodIE methodology flowchart.

3 Named entity recognition (NER) systems and Applications

H. Sintayehu (2020) [14] has been investigating methodology which compare two Semi-supervised approaches LP and EM for Ethiopian News Agency (ENA). The proposed methodology solves another issue in Named Entity Recognition Amharic languages tagging which is difficult for supervised learning methods when the data set is large. It applies to search engine Amharic languages applications. The queries are run on Ethiopian News Agency (ENA) text corpus this corpus consists of a total of 4700 sentences each sentence has 83 words approximately. Named entities under this corpus found five Topics are ‘‘Person’’, ‘‘Money’’, ‘‘Organization’’, ‘‘Date’’, ‘‘Location’’. The evaluation results EM is 64% F1-score and LP scores is 79% with 100% labeled dataset.

Popovski,G.(2019) [15] have proposed a FoodIE Algorithm which is used for found food entities and compared its performance with drNER. The FoodIE extract food recipes are performed in a food dataset for 5 classes: Snacks, Breakfast/lunch, Desserts, Dinner and Drink. This method is supported in the medical domain for knowing food precautions and ISOFOOD agency used these techniques for checking food quality and safety purposes. FoodIE corpus consisted of 200 food items, 100 used for manually semantic rules. The evaluation results F1 Score is 96%, Precision is 97.8%, Recall is 94.3% and FoodIE performs better as compared to drNER.

Furrer (2019) [16] have developed an OGER++ system focused on Biomedicine data mining which is used for main NER application to identify the medical names, chemical formulas and their relation. This tool provided Kb based and data driven elements to perform specific tasks in medical fields. This system is based in NER and CR where CR uses feed forward NN with some extra features like VC feature for vowels, common vocabulary, stop words and word embeddings only for n-gram words but in future they try to build for multi words. For system evaluated results are 71.4% F1 for NER and 56.7% F1 for CR and also text processes time is 9.7 per second or 0.9 per second in full t text data set these results are obtained from CRAFT corpus.

Table 2. Rule-based, Learning-based and Hybrid systems and applications.

Paper author	**Year & Publisher**	**Language /domain**	**Named Entities found**	**Technique used**	**Dataset used**	**Evaluation /results**
H. Sintayehu [14]	2020 and springer	Amharic	Person, Location, Organization, Money, Date	**Semi-supervised approach:** LP (Label propagation) and EM (Expected maximization)	Ethiopian News Agency (ENA) total sentences 4700 in corpus.	F1-score= 79%
Popovski,G. [15]	2019 and scitepress	English language /Food domain	Snacks, Breakfast / lunch, Desserts, Dinner, Drink	**Rule-based approach:** POS tagging use, manually created semantic rules	Data set collect from web, it has 200 sentences in text.	F1-Score=96 % Precision = 97.8% Recall =94.3%
Furrer[16]	2019 and BMC part Springer nature	English language / medical domain	Disease, Organism Molecular function, Biological process, Organ/tissue, Cell, line Cell. Cellular component, Gene or protein, Sequence, Chemical	**Hybrid Based approach:** dictionary-based annotator + corpus-based disambiguation + look-up strategy	CRAFT corpus, it has 67 full-text articles	**For NER:** F1-Score= 71.4% **For CR:** F1-Score= 71.4%

4 Comparison and analysis of different tools and algorithms for named entity recognition (NER) models

4.1 SpaCy

Spacy is a very famous open-source library in Python language which is built to perform many specific tasks in Natural Language Processing (NLP). It supports a variety of tasks, including Part of speech (POS)-tagging, Named Entity Recognition (NER), Text Classification, Dependency Parsing, Similarity measuring in text, lemmatization etc. [9]. It offers statistical models and Processing Pipeline for a variety of languages. Spacy tool is supported AI software explosion, that is utilized a hybrid of Hidden Markov Models (HMM), Maximum Entropy Models (MEMMs), and Decision Tree Analysis, these all models covered with a convolutional neural network to deal a huge number of datasets as well as involve new training data at the user's demand. It provides inbuilt NER models with particular entities such as person name, organization, time, location, etc [10].

4.2 StanfordNLP

The analysis on the natural language is made using one of the python libraries that is StanfordNLP. That is a rich package of tools to be utilized in a flow to get the list of words from the string contained in a string of Human Language. These tools could be used to create the parts of speech, morphological features, and dependencies of the phrases on the other, the astonishing thing in this that it could parallel work on more than 70 languages [11]. Some of the functionalities of the CoreNLP java packages could also be imported in this. The tool in the StanfordNLP also provides the implementation of the CRF sequence Model that is a classifier could be effectively used in NER well explained by [12]. StanfordNLP is java-based pipeline which provides natural language processing (NLP) techniques such as tokenization, sentiment analysis and Named Entity Recognition (NER).

4.3 TensorFlow

Tensorflow is an open source math library which is written in three different languages (such as Python, C++, and CUDA). It was developed by Google for machine learning applications or models such as neural networks. It is one of [13]. It is a data mining learning approach and it takes input in the form of numerical or hot encoding rather than text data. Tensorflow is used in many applications which are Google Translate, Text Summarization, Named Entity Recognition (NER) models and Speech Recognition, etc.

4.4 Apache OpenNLP

Apache OpenNLP is a library in Java which is built to do many specific tasks in Natural Language Processing (NLP). It supports a variety of tasks, such as Part of speech (POS) tagging, Named Entity Recognition (NER), Tokenization, chunking, Dependency parsing and Sentence Segmentation etc. Apache OpenNLP included perceptron approach and Maximum Entropy Models (MEMMs) well explained by [10]. For the purpose of NLP tasks, OpenNLP provides many services such as a set of predefined models which consist in different languages. It provides many features like the search string, given the option correctly spelled, and helps to translate one language into another language.

4.5 Comparison of NER different Tools and algorithms

Table 3. Advantages of SpaCy, StanfordNLP, TensorFlow and Apache OpenNLP for NER model

SpaCy	StanfordNLP	TensorFlow	Apache OpenNLP
1) SpaCy's NER Models have very less time about (µs) for prediction.	1) It supports multiple languages.	1) TensorFlow model's predication time is less than (ms).	1) Apache OpenNLP NER Models have very less time prediction it is about (ms).
2) Its modal provides F-score accuracy for every individual tag.	2) There is an improvement in CoreNLP and ease of use.	2) It applies into numerical form of text.	2) For the wrong prediction OpenNLP NER model provided very low accuracy.
3) It directly apply into text data or corpus.	3) It has larger memory so fast in processing.	3) The TensorFlow model in less size as compared to other models.	3) NER model cannot include the any unknown tokens or tag.
4) Information loss is decreased in every training iteration during training.	4) It is purely built in python.		4) It directly apply into text data or corpus.

Table 4. Disadvantages of SpaCy, StanfordNLP, TensorFlow and Apache OpenNLP for NER models

SpaCy	StanfordNLP	TensorFlow	Apache OpenNLP
The spaCy model in large size as compared to other models.	The StanfordNLP model in large size as compared to other models due to languages models	TensorFlow cannot find the relation between entities and tags it fellow's sequence of the tags.	OpenNLP model does not provide F-measure for all individual tag or label in dataset.
		For wrong prediction this model gives high accuracy.	

5 Evaluation

Evaluation is applied for checking the accuracy of tools that find the correct entity assigned according to tags defined. Basically, the evaluation of the performance of NER tools by using the Precision, Recall and F-measure. We evaluate NER tools by F1-score training data loss, time accuracy and Prediction probability. In our experiment NER tools apply into news corpus which is collected on the web. The news corpus consists of approximately 300 sentences. Experiment results are listed below.

F1-Calculation Formula

$$F1 - measure = 2\frac{Precision \times Recall}{Precision + Recall}$$

Recall Formula

$$Recall = \frac{TP}{TP + FP}$$

Precision Formula

$$Precision = \frac{TP}{TP+FN}$$

Accuracy Formula

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN}$$

Table 5. Experimental result of NER methods.

	SpaCy's	Standford	TensorFlow	OpenNLP
Training accuracy	100%	99.5%	99%	99%
Training loss	0.00000001029	0.0000000213 7	0.0229	0.00000142
F1-score	100%	94%	97%	96.5%
Prediction probability	100%	90%	96%	98.3%

NER Spacy tool provides 100% accuracy during training. The Stanford gives 99.5%, Tensorflow and OpenNLP show approximately 99% accuracy on training as shown in (Fig 2)

The NER TensorFlow method gives loss training 0.0229 value during training and Standord and OpenNLP loss training 0.00000002137 and 0.00000142. Spacy tool's loss data only 0.00000001029 value which is very less, that way it does not show in (Fig 3). The Stanford performs 94% F1-Measure, Tensorflow and OpenNLP show 97% and 96.5%. Spacy NER tool gives 100% F1- Score which is represent in (Fig 4).

Prediction Probability of Stanford tool is 90%. Tensorflow and OpenNLP give Prediction Probability accuracy 96% and 98.3%. The NER Spacy tool performs Prediction Probability is 100% , so that spacy NER method provides best and high results in each experiment For NER classification which is shown in (Fig 5).

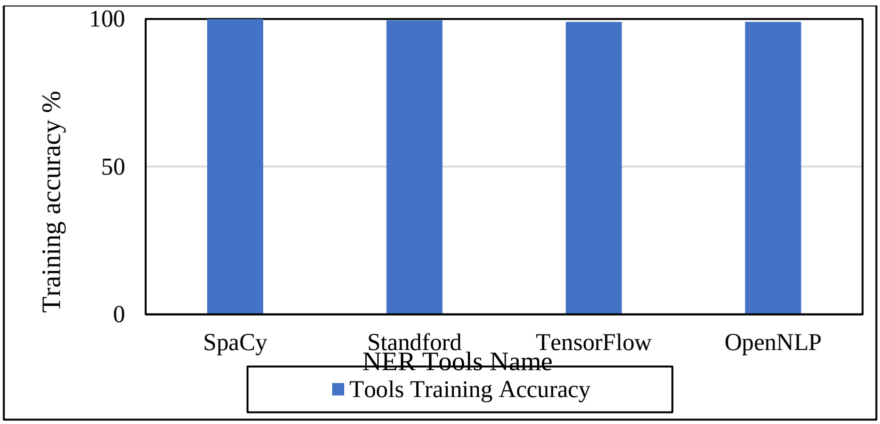

Fig. 2. Training accuracy of NER Tools.

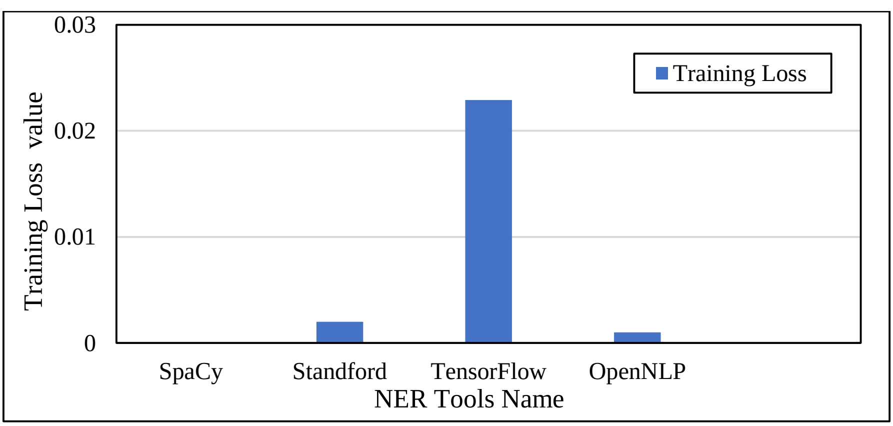

Fig. 3. Training loss of NER Tools.

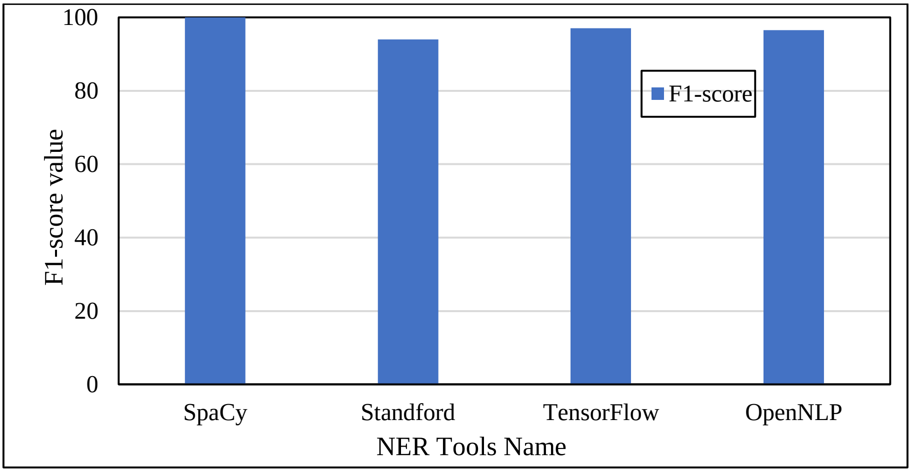

Fig. 4. F-measure of NER Tools.

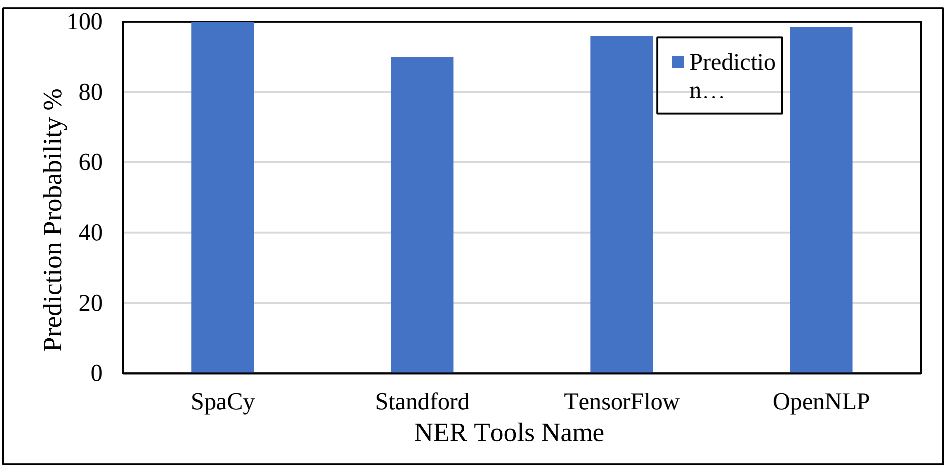

Fig. 5. Prediction Probability of NER Tools.

6 Future directions in named entity recognition (NER)

In the past years many start of the arts approaches were introduced that face many issues, challenges and are resolved for the purpose of NER systems. For NER modals highly depend on features selection therefore new clustering techniques are used to address noisy or sparse data problems.

Supervised machine learning algorithms need a large amount of dataset for training and testing of the models but it is a difficult challenge to collect a large number of datasets annotated from lower resources of languages, for instance Pakistan local languages. Unsupervised and Semi-supervised learning algorithms need few amounts of data set which is annotated. Hence, future researchers are focusing on exploring semantic related information about words and finding the semantic structure between words for named Entity Recognition systems.

In past studies had extracted only a few focuses such as name, time location etc. Therefore, new research are focusing on more fine entities which can help in many information retrieval applications. In NER systems linguistic features collection is costly, time consuming and memory space issues. So future research can work on statistical approaches applied in NER models for obtaining better results. They are also working to remove the ambiguity in the datasets in NER systems.

Rule-based models require specific languages and costly; they cannot easily transform into new languages. On the other hand, machine learning models are not easily portable from one system to another. So that new techniques are combined rule-based and learning based approaches to make for Hybrid approaches which give high quality result and less costly.

Conclusion

In this paper, we have tried to give the information about NER techniques, tools and algorithms in history, state-of-the-art current and few future working. In this article helps the new researchers to gain information about named entities issues and solutions. In this survey, introduction of Named Entity Recognition and also compared techniques, tools and algorithms. This paper provides a brief review of learning based systems, rule-based systems and hybrid NER systems. All this information is available in tabular form and also talks about these systems in detail. In this article we compared the different techniques which are Spacy, StanfordNLP, TensorFlow and ApacheOpenNLP in the news corpus. The Spacy gives good results and less predication time as compared to the other techniques. The evaluation measures on the basis of training accuracy, model size, time prediction, training loss data and F-measure discussed in detail. At the end of the paper some future directions are also provided so that this NER research field will continue to explore continue.

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