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A Semantic Approach for Entity Linking by Diverse Knowledge Integration incorporating Role-Based Chunking

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Abstract

Web-data has seen an exponential rise in the past few years. With the increase in the data on the web, the process of associating entities with required knowledge becomes extremely difficult. Linking entities not only becomes a tedious task but also requires the right association of knowledge with the right techniques. With the development of the Semantic Web in recent times, semantic strategies are required to represent, reason and link entities. In this paper, an entity linking approach that rightly associates personalities has been proposed. The proposed algorithm encompasses role-based chunking along with a fragmented parse tree generation. The proposed strategy performs Entity Linking by JSON fragmented parse tree generation and recommends the entities based on the semantic score generated by computing the concept similarity. The knowledge is supplied by a role-based Ontology modeled for various famous personalities. An accuracy of 89.77% is achieved for role-based entity linking which is much better and reliable than the existing strategies, especially when a large number of trials were conducted for the Indian Context.

1. Introduction

The volume of web-data created every day has seen a rise in the last decade. With all these increasing data it becomes very difficult to find a way to link all the available world wide web entities. Data is large but there is no sufficient knowledge to link all the data. Derivation of knowledge from the existing data is not just a challenge but is a need of the hour to improve the relevance of information retrieval on the Web. Entity Linking is a methodology of recognizing and disambiguating named entities to a knowledge base. Knowledge base containing the entities is required for Entity Linking, to which entity mentioned should be linked. Entity linking can either be end-to-end where in, processing a piece of text to extract the entities and further disambiguate these extracted entities to the correct entry in a given knowledge base. Also, the Disambiguation only approach takes gold standard named entities as input and disambiguates them to the correct entry in a given knowledge base.

High quality knowledge graphs are required in Natural Language Understanding for tasks like that of entity resolution and reasoning. Without the capability to reason about given information semantically, natural language understanding systems are only capable of shallow understanding. More complex learning tasks are required for machine learning. Thus, modeling high quality knowledge graphs is not just a pre-requisite but is highly essential. However, deriving such graphs is not a simple task. Assigning roles at first and further reasoning ontologies based on those roles is quite an

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impressive strategy, that has been proposed for entity linking. Impressive results are obtained by the incorporation of Knowledge graphs, but there needs to be competitive reasoning schemes in interpreting that knowledge graphs. Use of Folksonomies which pre-dominantly characterized Web 2.0 and the associated Social Web. Use of Folksonomies, enhances content visibility, search-ability, and classification. Broad folksonomy offers the user with a treasure of related data and tags, while narrow folksonomy information is very limited. Ontologies form the core structures in the Semantic Web [1] [2] [3] [4] that conceptualized Domain Knowledge [5]. A semantic bridge is composed of common knowledge [6] which makes knowledge-based systems quite advantageous. Ontologies represent knowledge as a collection of concepts within a domain and retrieve the relationships between these concepts. These models could be later re-used by users to reason out, validate, answer complex questions and further display information across the web. In this information age, it is almost impossible to find a proper relationship between various forms of data. Ontology creates a proper relation between these data. Ontology is extensible, more and more information can be added to already existing classes. Thus, a well-organized knowledge graph for natural language interpretation can be based on modeling and maintain high quality ontologies. The incorporation of web folksonomy data derived dynamically from Knowledge Bases, the modeling and use of role-based ontologies and their reasoning in a text-corpus based on the fragmented parse tree generation, to dynamically link the entities has been proposed.

Due to ever increasing web-data, it becomes tough and complex to retrieve relevant data and discover the right link among the large volumes of data that are scattered in the World Wide Web. Therefore, it becomes essential to formulate a precise methodology which addresses various attributes, objectives and concealed facts in the given data. Without such a methodology, retrieving relevant links from the vast data becomes obsolete and redundant. Incorporating the use of much reliable and intelligent semantic web and rightly using the techniques for natural language understanding and interpretations, can not only yield promising results but can become benchmark techniques for entity linking in an environment of highly dense web data. A reliable semantic model for linking various entities is formulated by the accumulation of knowledge from real world knowledge bases. The data in the text-corpus and the facts from knowledge are reasoned out by encompassing a role-based ontology that has been developed for personality entities. Techniques such as role-based chunking and fragmented parse tree generation are employed for natural language reasoning. However, concept similarity has been used for computing the semantic similarity. An efficient role-based chunking mechanism that successfully links various web entities from diverse domains comprising of personalities has been incorporated. An accuracy of 89.77% has been achieved where experiments are mainly focused on personalities in the Indian context, which is the best in class accuracy when Indian Context has been considered.

The remaining paper organization is as follows, section 2 provides a brief overview of the related literature of research that is conducted. Section 3 illustrates the proposed architecture. Section 4 describes the implementation in detail. Result and performance analysis is discussed in Section 5 and finally, the paper is concluded in section 6.

2. Related works

Ce Wang et al., [7] have proposed a strategy of knowledge-based information retrieval using relation extraction. This methodology incorporates semantic similarity for devising knowledge graph. Shi et al., [8] have structured an open world knowledge graph completion using the ConMask model. The above depicted model uses an entity named learning. Salehi et al., [9] have proposed a strategy for knowledge graph generation using link prediction which further incorporates relational knowledge graph. The proposed implementation subsumes relational facts and probabilistic interpretation is encompassed using strategic Bayesian approach. Padia et al., [10] have proposed a model that implements knowledge fact prediction using enriched tensor factorization. The above stated procedure takes into account the degree of entity graph for the knowledge graph generation.

Lu et al., [11] have formulated a methodology for information retrieval from knowledge graphs. The stated process uses a dynamic knowledge graph. The process is achieved by computing distance between a pair of topics the formulated knowledge graph. Paolo et al., [12] have devised a semantic approach for Entity Linking through small, labeled and weighted graphs. The graphs are weighted and structured by labelling nodes with relevance scores. This model combines language modelling techniques for implementation. Fang et al., [13] have put forward an approach of Entity Linking with deep reinforcement learning. The proposed model incorporates and breaks down global linking into the sequence decision problem for achieving reinforcement learning. Liu et al., [14] have put forth a collective entity linking strategy based on combining specific and diverse views. Further, the entire process of Entity Linking is reduced to Sub-Matrix searching problem.

Taniguchi et al., [15] have proposed a methodology for combining Entity Linking and evidence-based ranking for retrieving facts. This strategy includes TF-IDF. Apart from the above-mentioned model the proposed model also incorporates recognizing textual entailment strategy. Matthew et al., [16] have computed semantic similarity for linking entities using Convolutional Neural Networks. The above method also subsumes the n-gram model. Bhagavatula et al., [17] have formulated a methodology for Entity Linking based on the formulation of Web tables. The entire construction is done by computing the likelihood of co-occurrence of terms in the Wikipedia corpus. Wang et al., [18] have proposed a model for Entity Linking that is independent of the domain. This strategy makes use of Quantified collective validation. This model is exercised by reducing excessive linguistic analysis.

Hua et al., [19] have put forward an approach for Entity Linking that integrated social temporal context. This approach considers three features namely, Entity popularity, Entity recency, and user interest information. Yatskar et al., [20] have formulated Semantic role labelling for image understanding. This model assimilates image understanding using FrameNet, a verb and a role-based lexicon. Naveen et al., [21] have proposed an approach for Semantic role labelling employing the importance of the comma. This strategy also makes use of machine learning to obtain syntactic and discourse-oriented features. Meghana et al., [22] have proposed a novel approach for Semantic Role labelling encompassing FrameNet and crowd sourced lexical expansion. Zhu et al., [23] have proposed a semantic similarity computation strategy for computing the concept similarity between concepts in real-world Knowledge Graphs such as DBPedia and Wikipedia. The strategy proposes a graph based IC measure for computing IC on the basis for computing concept distributions over various instances. Deepak G et al., [24 - 29] have encompassed semantic similarity measures and efficiently performed semantic analysis for recommending web content. Pushpa et al., [30] and Leena et al., [31] have modeled ontologies for various domains using strategic review approach and a semantic alignment strategy respectively.

3. Proposed System Architecture

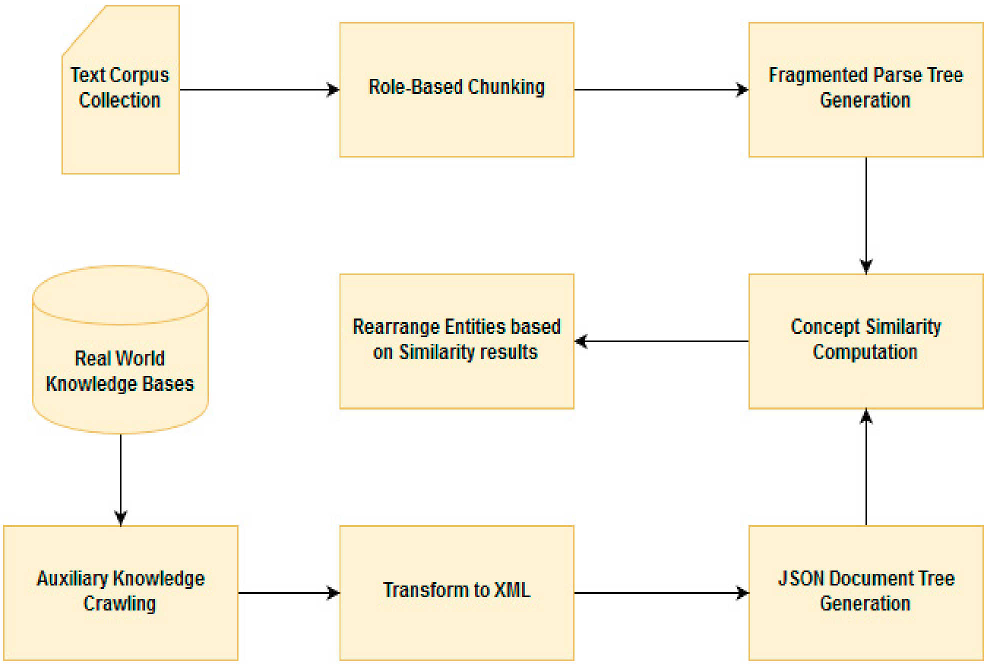

Figure 1: The architecture of the proposed role-based entity linking

The architecture of the proposed system is depicted in Figure 1 and the exact same procedures have been adopted for role-based entity linking. Initially, the text corpus is created from various web sources. Since the mainstream strategies focus on preparing a text corpus for personalities, the Wikipedia data is targeted from the personalities Wikipedia data. Apart from this, the data is collected from reliable websites and is formulated from various articles across the web and is formed into the text corpus. This data consists of both true and false facts and has within all the various entities that are to be linked as the final output of the implementation. The web corpus, comprises of web data and is in the format of a text file (.txt) and serves as the primary source for performing role-based chunking for entity linking.

The role-based chunking is mainly focused on applying shallow parsing on the text-corpus, based on the unique roles identified by the personalities. The sentence is recognized and based on using roles as a marker, a fragmented-parse tree is generated. The sentences are pre-processed by tokenization and stemming and further, roles are identified by computing the concept similarity. Once the concept similarity has been computed, the roles are validated and based on the roles, the fragmented parse trees are generated. The reason for focusing on the fragmented parse trees and not regular parse trees is that chunking is adopted than regular parsing. Chunking serves as flow breakers for unique roles depending on the personalities. This clearly generates an implicit context, which can further be validated, using modeled role-based ontologies. Just before validation, POS tagging is done for the various nodes in the fragmented parse tree. This is to ensure that, each node is a proper noun or a verb. If it's a proper noun, then the names are recognized as primary entities and if not, then, the words are validated with the roles. This strategy is called role-based chunking. For each node in the parse tree using appropriate queries, an auxiliary knowledge is crawled. Further, this auxiliary knowledge from real-world knowledge bases, comprising of facts is transformed into an XML file format and is then transformed into a JSON document tree by specifying various attributes.

The role-based ontology is modeled by depicting the famous personalities as the primary entities and their closely related real-world entities are modeled as secondary entities. The roles are assigned between the entities. The assumption is that the roles are rightly assigned among the primary and secondary entities. Once the fragmented parse tree nodes and the auxiliary knowledge is aligned, the knowledge validation based on the role-based ontology is achieved by computing the concept similarity. Finally, the similarity score is checked between each node in the formulated JSON document tree and the input Role-Based ontology knowledge graph. The similarity score is computed using the strategy depicted in [23]. Any considerable and good concept similarity score. Based on the increasing order of semantic score, the linked entities are arranged and are recommended or listed out.

4. Implementation

The implementation of the proposed architecture is completed using Python 3.7.1 using Jupyter Notebooks as IDE. The implementation is done using NLTK. The implementation was carried out on an intel i5 processor and includes 8GB of RAM. The entire implementation was pioneered by the creation of the text corpus using various web articles and complete information gathering using all the Wikipedia data that is available. The next task was the renovation of the text corpus into a knowledge base. The subsequent task was the introduction of the natural language tool-kit and using sent_tokenize and word_tokenize tokenization and lemmatization of the text file is done and a structured data set is obtained. In the next step, all the tokenized words are tagged using POS_tag(Ws) that is inbuilt in NLTK. This process results in the formation of a chunked parse tree (Cs). Using this chunked parse tree, a role-based ontology is formulated which is used a knowledge graph in the proposed model. Subsequently, an auxiliary knowledge base is crawled using auxiliary folksonomies, DBPedia and YAGO knowledge based and this auxiliary knowledge is transformed into an XML file format which is further converted into JSON. Now concept similarity is implemented between the devised JSON tree and the ontology that is shaped. Based on the similarity scored, the entities linked are arranged. Ultimately these linked entities are recommended. The threshold of 0.25 has been considered for computing concept similarity as the threshold normally correlates to minimum support which is 0.2 in traditional applications. In order to keep the threshold values closer to the minimum support, a threshold of 0.25 has been chosen. The Algorithm for Role-Based Entity Linking is depicted in Table 1.

A knowledge graph represents many facts, through the use of an indicated edge which is often referred to as a directed link. There can be many facts connected to each edge, creating this a directed multigraph. For example, looking at the above example of a knowledge graph embodied in Figure 2, one can depict about the query "Is Karan Johar a Director?" by simply walking through and having a look at the graph, starting at "Karan Johar" and walking to "Director", examining edges and concepts along the path. Knowledge graphs tend to be quite large and complex in more complex scenarios. That amount of knowledge helps and enables us with the use of these graphs to effortlessly reason about semantic connections for jobs such as augmenting business-relevant data and by helping to resolve entities. Now that a comprehensive idea on a knowledge graph is obtained, a small insight into a knowledge base is vital. A knowledge base is generally referred to as a database which is mainly used for knowledge sharing and also management. Collection, organization, and retrieval of knowledge are facilitated by the knowledge base. Storing data and finding solutions for further problems using data from previous experience stored as part of the knowledge base is done by Knowledge graphs.

A good entity linking methodology must be able to perform tasks like Information retrieval, Information Extraction, Question Answering, Content Analysis, Knowledge Base Population.

Table 1. Algorithm for Role-Based Entity Linking

Input: Text-Corpus, Auxiliary Knowledge A_k and Role Based Ontology O_r
Output: Entities Linked Based on Roles with validations.

begin
Step 1: Tokenize & lemmatize the text-corpus to obtain a List of words $L_{w.}$
Step 2: POS_tag(L_W) to obtain POS tagged HashSet (Hpos).
Step 3: while ($H_{pos.}$next()!=NULL)
If ($H_{pos.}$value !=NN)
Set roles← $H_{pos.}$ value
Chunk H_{pos}.contents() to obtain chunked parse tree(C_s).
Step 4: for each item in C_s
Crawl A_x using an appropriate crawler
Step 5: while ($A_{k.}$next()!=NULL)
Transform A_k as XML Tags and obtain a JSON Document Tree Jp
Step 6: for each item in Jp
cs= concept similarity ($J_{p.}$current() ,roles)
if(cs<0.25)
add matching roles r_m← roles.current()
compute as cs1 concept similarity ($r_{m.}$current(), O_r)
if(cs1<0.25) //Role Based Valdation
Recommend cs1. $H_{pos.}$key() and append $O_{r.}$Entity()
end

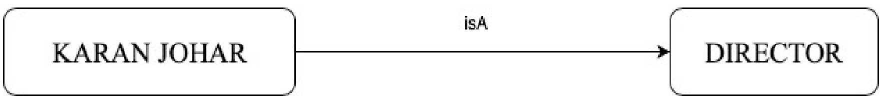

Figure 2: Depiction of Assigning Roles to a Person Entity

When all the nodes of an ontology are assigned with definite roles. The main objective of a role-based ontology is to denote all the available roles on which the entire process of Entity Linking is being implemented. The method of formulating a role-based ontology can be explained with a simple example such as: “Rita drove from Kochi to Bangalore”. In the above example, there are a total of three proper nouns. But when the person Rita is considered there are two objects with respect to that person, which are a Source and a Destination. Here Kochi has a role of Source in the context of Rita, and Bangalore plays the role of Destination. The representation of this sentence in the form of an ontology can only be done when all the roles are properly assigned in the context of the root node. This is how the entire modulation of the ontology below is done.

To understand the complexity and get into the insights of the Natural Language Understanding, it’s necessary to define what actually a knowledge graph means. A knowledge graph is a graph where each node denotes an entity and each edge is engaged and denotes an association between the corresponding entities. Entities are usually in the form of proper nouns and sometimes concepts (e.g. Karan Johar and Movie, respectively), with the ends demonstrating verbs (e.g. is A). Together, all these entities form giant networks that determine semantic information. For instance, determining the fact that “Karan Johar is a Director” in the knowledge graph is formulated by storing two ends, one for “Karan Johar” and one for “Director” with a directed edge beginning with Karan Johar and directing to Director of type “isA”.

Figure 3 depicts a fragment of the role-based ontology that has been that has been formulated for various famous personalities like Karan Johar, who is a Director, Actor, Writer, Producer, Distributor, etc. Figure 3 is just a fragment of the ontology that was formulated for many other famous personalities in varied genres having professions like Authors, Cinematographers, Writers, Directors, Singers, Politicians, Hosts, Judges, Actors, Radio Jockeys, Dancers, Novelists and so on. The role-based ontology that was considered for experimentation comprised of the various roles of the personalities mentioned in Table 2 along with the details and roles of 57 other personalities. The role-based ontology was mainly developed for personalities of Indian Context. However, a few prominent personalities of the West, predominantly the American and the British personalities were also considered

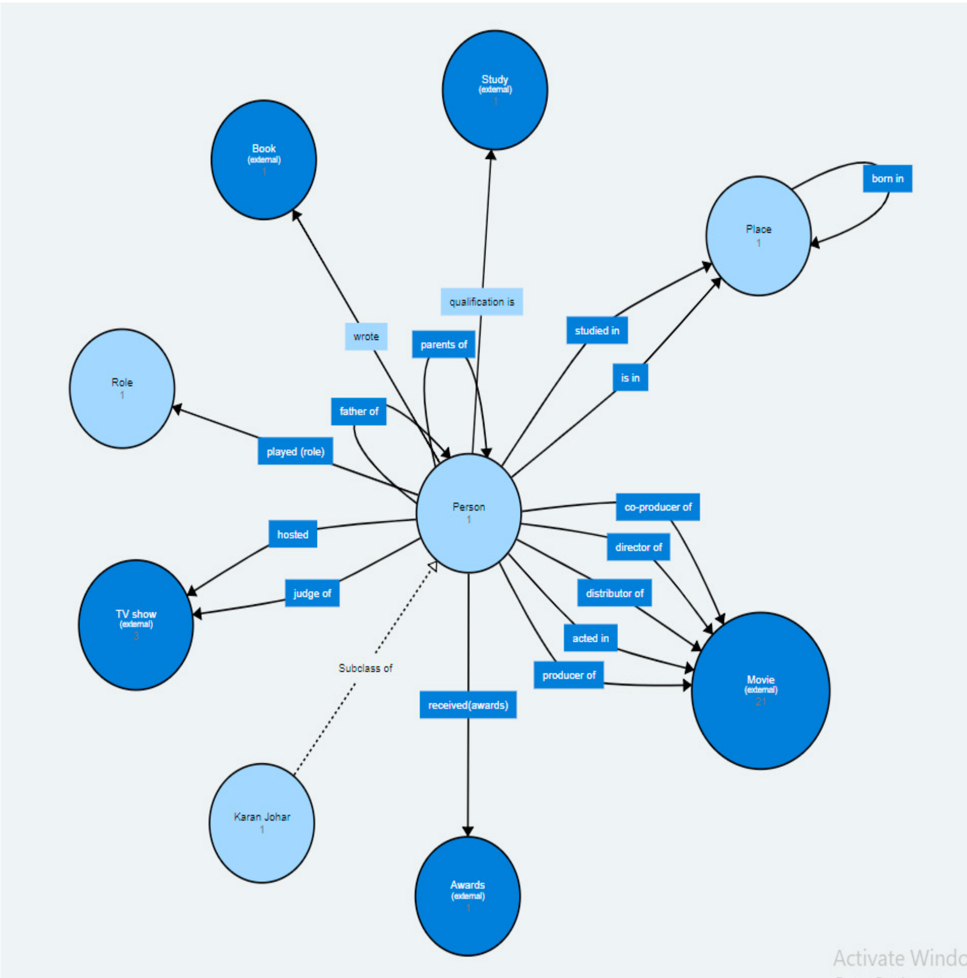

Figure 3: Fragment of Role-Based Ontology considered for experimentation

However, the experimentation was mainly focused on personalities in the Indian Context. The reason is that there are several entity linking algorithms that correctly link the personalities from the West owing to their much available knowledge. But those algorithms lack the entity linking capacity for the personalities in the Indian Context. To overcome this, the knowledge of Indian Personalities was rightly modeled. The Ontology comprised of 71 unique personalities as primary entities with 187 unique roles. However, certain roles were shared by many other personalities. Also, 48 secondary entities were included for experimentation as well. The secondary entities are those relevant entities that could be possibly linked to the primary entities. For, instance, the entity “TV Show” can be linked to the primary entity “Karan Johar”. In Figure 3 the primary entities (Personalities) are depicted by light blue and a dark shade of blue denotes the secondary entities. This is mainly done to enhance the clarity of the primary entity, by populating the entity set.

5. Results and Performance Evaluation

The experimentation was conducted for datasets crawled from Wikipedia data and other prominent web pages containing the information of famous personalities. The dataset was harvested in a way such that the Web information relevant and irrelevant to the famous personalities listed out in Table 2, was crawled using a customized crawler. The reason was including irrelevant information in the data corpus collected was to ensure the reliability of the proposed role-based entity linking algorithm. The crawled data was formulated into a text corpus and was considered for experimentation. The noisy deviated data was considered in a way such that, it is totally in contrary to a very low degree of differentiation to the personalities in Table 2 was also added, to ensure the correctness of entity linking. The percentage of Accuracy was used as the standard metric and is represented by Eq. (1).

$$Accuracy(\%) = \frac{No.of\ correctly\ linked\ Entities}{Total\ number\ of\ entities\ linked} * 100. \tag{1}$$

The performance of the proposed algorithm has been depicted in Table 2. It is clearly evident that the proposed strategy identifies and links entities and has a high success rate in correctly identifying the roles and perform role-based chunking for linking entities. One of the sole and primary reasons for obtaining a high percentage of accuracy is that the proposed strategy integrates knowledge from real-world knowledge bases like the Wiki and DBPedia. This is a clear indication that the proposed approach supplies facts in the form of Knowledge. Moreover, the results are tabulated for personalities mainly in the Indian context. However, personalities from the west are also included to compute the diversity and efficiency of the proposed approach. Also, characters like Dev Patel who is of Indian origin but whose work is significantly in the West are also considered. It is clear that a 100% accuracy is achieved for Karan Johar, Rabindranath Tagore, R K Narayanan, and Sarojini Naidu. The reason for a 100% accuracy could be that a sufficient amount of knowledge would have been extracted from the knowledge bases and the role-based ontology was also well defined. S S Rajamouli has the least accuracy percentage of 80%, and the obvious reason for this could be the knowledge extracted for S S Rajamouli would have been sparse. However, for other personalities, the accuracy ranges between 83.33 and 91.66. Despite the personalities being in the Indian Context, from the West as well as Indian Origin person who has contributed in the West, the algorithm performs well yielding an accuracy of 89.77% which is definitely a best-in-class accuracy. The encompassment of role-based chunking by the modeling of role-based ontologies, fragmented parse tree generation and dynamic composition of knowledge
from real-world heterogeneous knowledge bases has resulted in a high accuracy percentage.

Table 2. Performance Measures of the Proposed Algorithm

Experimentation Entities (Famous Personalities)	**No. of correctly identified roles**	**No. of roles linked incorrectly**	**Accuracy %**
Karan Johar	10	0	100
S S Rajamouli	4	1	80
Madhuri Dixit	5	1	83.33
Rabindranath Tagore	3	0	100
Gautam Vasudev Menon	10	2	83.33
David Archuleta	15	3	83.33
Helen Mirren	7	1	87.5
Sarojini Naidu	5	0	100
Karan Thapar	10	2	83.33
R K Narayan	4	0	100
Oprah Winfrey	8	1	88.88
K R Narayan	13	2	86.66
Whoopi Goldberg	11	1	91.66
Dev Patel	8	1	88.89

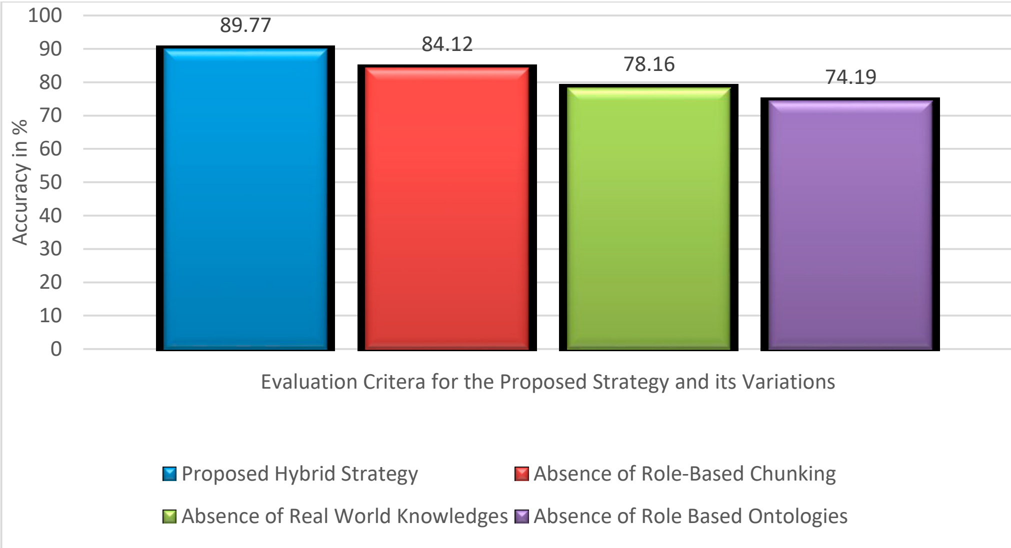

Figure 4: Performance Comparison of the Proposed Hybrid Approach in by criteria variations

From figure 4, it is clearly evident that the proposed strategy yields an overall accuracy of 89.77 % owing to the various strategies that have been incorporated into the proposed approach. However, in order to compare the effectiveness of the proposed strategy based on various criteria that have been encompassed, the proposed approach is tested by criteria variations. In the Absence of Role-Based Chunking, the performance of reduces from 89.77% to 84.12%. The main reason for the decrease in the performance is that role-based chunking clearly constructs parse trees based on various roles and when role-based chunking is not imbibed, then the performance falls down by 5.65%. However, in the absence of Real-World Knowledge, there is a huge dip from 89.77% to 78.16%. The reason is mainly due to the fact that real-world knowledge provides facts that have been verified and is a key player towards affecting the overall accuracy for entity linking. However, the role-based ontologies are the most vital in the proposed system as without their presence, the accuracy falls from 89.77 % to 74.19%. The role-based ontologies depict the roles and their importance for the participating entities. Thereby their presence is strongly required and they play a key role in influencing the performance of the proposed system. Thus, it is clearly inferable from figure 4 that the proposed Hybrid methodology has the best-in-class accuracy and the importance of each technique in the hybridization is important.

6. Conclusions

A novel semantic strategy for Entity Linking has been proposed for various personalities who are famous. The proposed strategy incorporates role based chunking and fragmented parse tree generation. Entity Linking has been achieved for a text corpus by modeling a role-based ontology and further performing a chunking mechanism. A diverse knowledge integration by accumulating knowledge from real-world factual knowledge bases like Wiki and DBPedia has been encompassed. The experimentations are conducted for personalities predominantly in the Indian Context. However, a few instances from the West are also been considered. The algorithm is credible for personalities irrespective of their context or place of origin. However, the proposed strategy yields good results even for the Indian context due to knowledge aggregation. The proposed strategy yields an overall accuracy of 89.77% which is definitely a best-in-class strategy for Entity Linking when personalities from the Indian Context are majorly included for experimentation. As a part of the future work, dynamic inferencing mechanisms for inferring ontologies from the unstructured web data based on new semantic schemes can be proposed.

References

[1] Deepak, G., and Kasaraneni, D., (2019) "OntoCommerce: an ontology focused semantic framework for personalised product recommendation for user targeted e-commerce." International Journal of Computer Aided Engineering and Technology (IJCAET), 11(4/5), pp.449-466.

[2] Deepak, Gerard, and S. J. Priyadarshini. (2016) "Onto tagger: ontology focused image tagging system incorporating semantic deviation computing and strategic set expansion." Int. J. Comput. Sci. Bus. Inform 16, no. 1.

[3] Pushpa, C. N., Gerard Deepak, J. Thriveni, and K. R. Venugopal. (2016) "A Hybridized Framework for Ontology Modeling incorporating Latent Semantic Analysis and Content based Filtering." International Journal of Computer Applications 150, no. 11.

[4] Deepak, Gerard, and J. Sheeba Priyadarshini. (2018) "A Hybrid Semantic Algorithm for Web Image Retrieval Incorporating Ontology Classification and User-Driven Query Expansion." Advances in Big Data and Cloud Computing 645: 41.

[5] Li, Juanzi, Jie Tang, Yi Li, and Qiong Luo. (2008) "Rimom: A dynamic multistrategy ontology alignment framework." *IEEE Transactions on Knowledge and data Engineering* 21, no. 8: 1218-1232.

[6] Mascardi, V., Locoro, A., and Rosso, P. (2009) Automatic ontology matching via upper ontologies: A systematic evaluation. *IEEE Transactions on knowledge and data engineering*, *22*(5), pp.609-623.

[7] Wang, Ce, Hongzhi Yu, and Fucheng Wan. (2018) "Information Retrieval Technology Based on Knowledge Graph." In 2018 3rd International Conference on Advances in Materials, Mechatronics and Civil Engineering (ICAMMCE 2018). Atlantis Press.

[8] Shi, Baoxu, and Tim Weninger. (2018) "Open-world knowledge graph completion." In Thirty-Second AAAI Conference on Artificial Intelligence.

[9] Salehi, Farnood, Robert Bamler, and Stephan Mandt. (2018) "Probabilistic Knowledge Graph Embeddings."

[10] Padia, A., Kalpakis, K., Ferraro, F., and Finin, T. (2019) "Knowledge Graph Fact Prediction via Knowledge-Enriched Tensor Factorization." arXiv preprint arXiv:1902.03077.

[11] Lu, Yumao, Ling Li, and L. E. E. Che-Hsien. (January 24, 2019) "Facilitating discovery of information items using dynamic knowledge graph." U.S. Patent Application 15/776,053 filed.

[12] Cifariello, Paolo, Paolo Ferragina, and Marco Ponza. (2019) "Wiser: A semantic approach for expert finding in academia based on entity linking." Information Systems 82: 1-16.

[13] Fang, Zheng, Yanan Cao, Dongjie Zhang, Qian Li, Zhenyu Zhang, and Yanbing Liu. (2019) "Joint Entity Linking with Deep Reinforcement Learning." arXiv preprint arXiv:1902.00330.

[14] Liu, Ming, Gu Gong, Bing Qin, and Ting Liu. (2019) "A Multi-View–Based Collective Entity Linking Method." ACM Transactions on Information Systems (TOIS) 37, no. 2: 23.

[15] Taniguchi, Motoki, Tomoki Taniguchi, Takumi Takahashi, Yasuhide Miura, and Tomoko Ohkuma. (2018) "Integrating Entity Linking and Evidence Ranking for Fact Extraction and Verification." In Proceedings of the First Workshop on Fact Extraction and VERification (FEVER), pp. 124-126.

[16] Francis-Landau, Matthew, Greg Durrett, and Dan Klein. (2016) "Capturing semantic similarity for entity linking with convolutional neural networks." arXiv preprint arXiv:1604.00734.

[17] Bhagavatula, Chandra Sekhar, Thanapon Noraset, and Doug Downey. (2015) "TabEL: entity linking in web tables." In International Semantic Web Conference, pp. 425-441. Springer, Cham.

[18] Wang, Han, Jin Guang Zheng, Xiaogang Ma, Peter Fox, and Heng Ji. (2015) "Language and domain independent entity linking with quantified collective validation." In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, pp. 695-704.

[19] Hua, W., Zheng, K., and Zhou, X., 2015, May. Microblog entity linking with social temporal context. In Proceedings of the 2015 ACM SIGMOD International Conference on Management of Data (pp. 1761-1775). ACM.

[20] Yatskar, Mark, Luke Zettlemoyer, and Ali Farhadi. (2016) "Situation recognition: Visual semantic role labeling for image understanding." In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 5534-5542.

[21] Arivazhagan, Naveen, Christos Christodoulopoulos, and Dan Roth. (2016) "Labeling the semantic roles of commas." In Thirtieth AAAI Conference on Artificial Intelligence.

[22] Kshirsagar, M., Thomson, S., Schneider, N., Carbonell, J., Smith, N.A., and Dyer, C. (2015) "Frame-semantic role labeling with heterogeneous annotations." In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 2: Short Papers) (Vol. 2, pp. 218-224).

[23] Zhu, G., and Iglesias, C.A. (2017) "Computing semantic similarity of concepts in knowledge graphs." IEEE Transactions on Knowledge and Data Engineering, 29(1), pp.7285.

[24] Deepak, Gerard, and J. Sheeba Priyadarshini. (2018) "Personalized and Enhanced Hybridized Semantic Algorithm for web image retrieval incorporating ontology classification, strategic query expansion, and content-based analysis." Computers & Electrical Engineering 72: 14-25.

[25] Deepak, Gerard, and Sheeba Priyadarshini. (2016) "A hybrid framework for social tag recommendation using context driven social information." International Journal of Social Computing and Cyber-Physical Systems 1, no. 4: 312-325.

[26] Deepak, Gerard, Ansaf Ahmed, and B. Skanda. (2019) "An intelligent inventive system for personalized webpage recommendation based on ontology semantics." International Journal of Intelligent Systems Technologies and Applications 18, no. 1-2: 115-132.

[27] Deepak, G., Shwetha, B.N., Pushpa, C.N., Thriveni, J., and Venugopal, K.R. (2018) A hybridized semantic trust-based framework for personalized web page recommendation. International Journal of Computers and Applications, pp.1-11.

[28] Deepak, Gerard, J. Sheeba Priyadarshini, and MS Hareesh Babu. (2016) "A differential semantic algorithm for query relevant web page recommendation." In 2016 IEEE International Conference on Advances in Computer Applications (ICACA), pp. 44-49. IEEE.

[29] Deepak, G., and Z. Gulzar. (2017) "Ontoepds: Enhanced and personalized differential semantic algorithm incorporating ontology driven query enrichment." Journal of Advanced Research in Dynamical and Control Systems 9, no. Specia: 567-582.

[30] Pushpa, C. N., Gerard Deepak, J. Thriveni, and K. R. Venugopal. (2015) "OntoCollab: Strategic review oriented collaborative knowledge modeling using ontologies." In 2015 Seventh International Conference on Advanced Computing (ICoAC), pp. 1-7. IEEE.

[31] Giri, G.L., Deepak, G., Manjula, S.H., and Venugopal, K.R. (2018) " OntoYield: A Semantic Approach for Context-Based Ontology Recommendation Based on Structufre Preservation." In Proceedings of International Conference on Computational Intelligence and Data Engineering (pp. 265-275). Springer, Singapore.