Semantic Approaches Survey for Job Recommender Systems

Assia Brek, Zizette Boufaida

LIRE Laboratory, University of Constantine 2 Abdelhamid Mehri, Constantine, Algeria

Abstract
Newly, the e-recruitment phenomenon has been widely spread, which led to the increase of job descriptions online and caused a remarkable growth in the number of jobs seekers sending their resumes searching for new opportunities. This enormous amount of information makes finding the appropriate job/candidate a difficult process. The recommender system technology is designed to help users find items that match their interests. Therefore, several recommendation approaches have been proposed to improve the e-recruitment process. Semantic technologies have been proposed to guide document processing and automatic matching, improving the job recommendation results. The research reported in this paper is a literature review of the semantic e-recruitment approaches; we spotlight the benefits of exploiting the semantic technologies in different aspects (information extraction and matching) in this context. Furthermore, we classified those approaches by comparing the semantic technologies used the advantages and disadvantages of each approach.

Keywords
E-recruitment, Job recommender system, Semantic approaches, Information extraction, Matching, Ontologies.

1. Introduction

Recently, the internet has become the first destination as a recruitment market, which increased the number of job offers and resumes online. Recommendation systems are proposed to help users filter this massive amount of information, selecting the best candidate or the relevant offer.

Recommender systems are software and techniques aimed at suggesting products that interest users, based on studying their behaviors (their product research) and their profiles [1]. In e-recruitment, the job recommender system has been proposed to handle the issue above for job seekers and enterprises. As a recommender system, the job recommender system can retrieve a list of job positions that satisfy a job seeker's desire or a list of talented candidates that meet the requirement of a recruiter by using the recommendation technology.

The mainstream approaches to recommender systems are classified into four categories: knowledge-based (KB), Content-Based Filtering(CBF), Collaborative Filtering(CF), and Hybrid approaches. Based on several researches and comparative studies in the e-recruitment problem [2-5], the content-based methods are more suitable for this context than other traditional methods, view to the necessity of examining the content of documents (resumes/offers).

Since the primary purpose of the semantic web is to enrich the syntactic structures of the current web with their semantic content, exploiting its technologies in the context of e-recruitment seems beneficial, especially to ensure an automatic treatment of documents and reconciliation between job requests and offers. Several approaches take into consideration the semantics of the document. This paper presents a survey of existing semantic methods for job recommender systems and proposes a new classification of those approaches based on what and how semantic technology is used.

The rest of the paper is organized as follows. In section 2, a formal definition of job recommendation is presented. In section 3, we cite the semantic-based approaches and the main uses of semantic technologies in different process steps. Section 4 is devoted to discussing the proposed approaches by showing the pros and cons of each one. Finally, Section 5 concludes the paper.

2. Problem statement

In this paper, we mean by job recommendation, on the one hand recommending job offers for a job seeker, and on the other recommending candidates for a given job. We can define the job recommendation problem as identifying a function $F(r,j)$, that takes an:
- Input:
    - $R = \{r\}$, set of user resumes.
    - $J = \{j\}$, set of job offers.
    And gives:
- Output:
    - $\forall r \in R$, the system should generate a ranked list (TopN) that recommend jobs for user according to their resume (r).
    - $\forall j \in J$, the system should generate a ranked list (TopM) that recommend candidates for job post (j).

Recommend a job or a candidate employing the content-based approach means exploiting the job offers description and candidates' resume content to find TopN/TopM list. First, the information extraction phase extracts a list of domain entities from offers (E_j) and resumes (E_r). Next, the matching phase takes charge to compare entities from (E_j) with (E_r) where the matching value is defined as:

$$match(Ej, Er) = \frac{Ej \cap Er}{Ej}$$

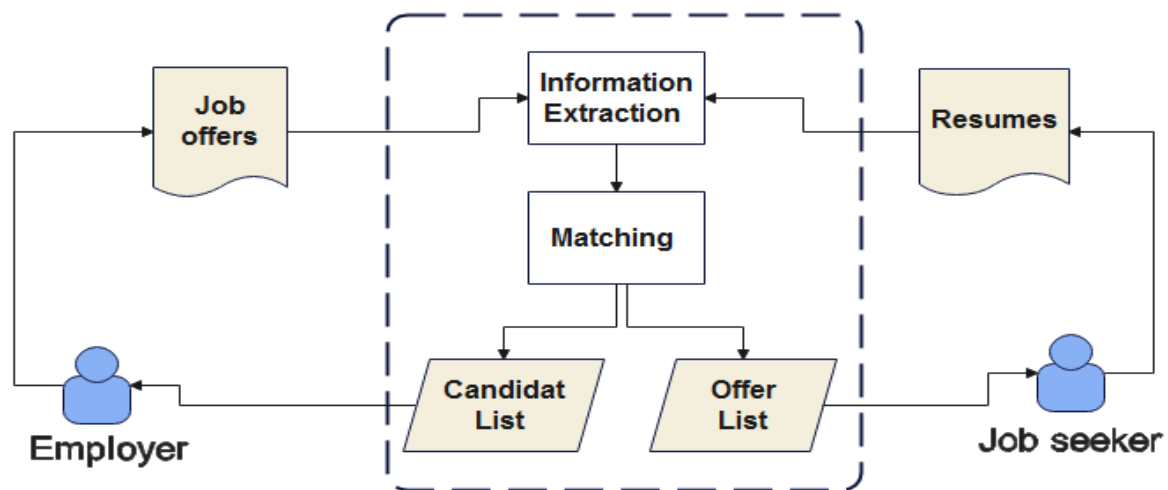The offers/candidates list is ranked based on the matching value.

Figure 1. Architecture of Job Recommender System.

3. Semantic approach

Semantic web technologies aim at enriching the web's documents with their semantic content facilitating the use, access, and intelligent processing of this content. Therefore, in the e-recruitment context, we can define semantic-based approaches as content-based approaches that use semantic technologies to process document content. Several approaches consider the semantics of the documents (resumes and offers) and exploit semantic technologies in two main aspects: information extraction and matching strategies.

3.1. Information extraction methods

Resumes and offers documents are mainly published as free text that is difficult to process automatically. Therefore, information extraction is a preliminary phase in job recommendation. Information extraction is an automatic technique for identifying entities from unstructured and/or semi-structured documents, intending to make them machine-readable. Semantic technology has recently been applied to guide the information extraction process [6,7]. Semantic methods mainly exploit semantic references like knowledge graphs (KG) and domain ontologies to extract entities or relations from unstructured text. Based on the previous e-Recruitment works, the information extraction methods that exploit semantic technologies can be divided into three categories: entities recognition, semantic annotation, and semantic graph extraction.

3.1.1. Entities recognition

Entities recognition is the task of identifying domain entities from unstructured text using different methods such as NLP, machine learning, and statistical/structural rules. Semantic resources are also exploited to identify domain entities [8]. In [9], a domain ontology is used as a semantic dictionary to extract information from resumes; the document content was segmented into sentences; next, the ontology concepts are used to detect domain entities, and only the ontology concepts are identified. Suppose the used ontology does not cover all the domain entities, using this last may cause losing information. Therefore, work in [10] defined semantic patterns to identify and extract domain entities, a JAPE rules are defined based on the document structure and domain dictionary to extract entities such as skills, experience, and diploma from both resumes and offers. In the same way, work in [11] presents the combination of NLP and semantic technologies to extract segments that represent skills, experiences, and other information about expertise such as name, position title, date of recruitment, ...etc. The extraction is done via employing NLP techniques such as document splitting, n-gram tokenization, and Named Entity Recognition, using a knowledge base (DICE [2] and O*NET [3]).

The main idea is to use semantic resources like Ontologies, Thesaurus, and knowledge graphs to identify and extract domain entities from job offers and resumes, ignoring the importance of extracting relations from the documents, which considered valuable data for the matching phase. In addition, this method does not grant any formal presentation of the extracted information.

3.1.2. Semantic annotation

Semantic annotation is the task of linking entities from text with their semantic description using external resources such as domain ontology and KG, which aids in disambiguating the document's content for automatic processing [12,13]. Semantic annotation is proposed as a solution to extract semantic information from documents. [14] Presents an approach based on semantic annotation of CVs and job offers for automating recruitment on the web. Authors exploit domain ontology via GATE API to select domain entities and link them with the ontology concepts, which deliver a formal presentation of the document content, enriching it with semantic metadata. The E-Rec-Sys [15] is an example of a tool that uses an ontology to annotate the different kinds of information in a resume, like names, diplomas, and languages. The first step of the E- Rec-Sys system consists of splitting the documents into words; then, utilize the ontology called ERECO (e-recruitment Ontology) to annotate the data automatically. In the same way, work in [16] exploited the HR-Ontology from work presented in [17] to annotate CVs and offers. The resulted annotation is the primary input in the matching phase. Moreover, in [18], the authors proposed a system SAJ that defined semantic patterns using JAPE to

---

[2] http://www.dice.com/skills.

[3] http://www.onetcenter.org/taxonomy/2010/list.html.

extract entities from job offers, then a domain ontology have been used to annotate those entities and link them with semantic relations.

The works mentioned above deliver semantic annotation approaches based mainly on a domain ontology; the process is done manually or semi-automatic using annotation tools like GATE API. The benefit of this method is linking entities from documents with ontology concepts, which offer a reasoning base to infer information, not mentioned directly in the document.

3.1.3. Semantic Graph extraction

More recently, several works propose to extract information as a semantic graph that presents the content as interlinked entities [19,20], allowing the automatic matching of resumes and offers. Work in [21] presented an automatic online recruitment system that exploits semantic resources to capture the semantic aspects of resumes and job posts. WordNet [22] and YAGO3[23] KG are used to capture terms from resumes and offers after segmenting them into sentences; then, the extracted entities are linked with semantic and taxonomic relations (synonymy relation and hypernymy relation), creating a semantic network that reflects the primary information of resumes and offers. Since the used resources of knowledge are KGs with general data, the extracted entities are linked with general relations and not specific to the domain. Therefore, in [24] authors proposed an e-recruitment system that exploits domain ontology to present the resume/ offers as a sub-ontology of related instances (semantic graph), where the matching phase is based on comparing the offer ontology with the resume ontology; in this work only the instances and relations presented in the ontology are extracted from resumes and offers. Where, the quality of the extracted data depends on the knowledge of the used ontology.

3.2.   Semantic matching

Matching aims to determine how well a given resume fits a requested job by searching for the required information in the acquired information. Several techniques/approaches have been employed in this aspect, such as latent semantic analysis (LSA) [25], structured relevance models (SRM) [26], and fuzzy distance metrics [27]. However, semantic-based approaches achieve good, matching results in the e-recruitment domain. Authors in [28] define semantic matching as a function $(\mu1 \times \mu2 \implies R)$ that associates the degree of correspondence for the entities $\mu1$ and $\mu2$ to a score $s \in R$ in the range [0, 1], where a score of 0 states no correspondence at all and 1 for total correspondence of the entities $\mu1$ and $\mu2$. Estimate the degree of correspondence for entities based on two different perspectives: using semantic similarity measures and semantic relatedness measures.

Semantic similarity is determining the proximity between two entities through taxonomic relations. Semantic similarities includes mainly "is-a" relations. For example, java is a programing language.

Semantic relatedness includes any relation between two terms. This measure considers the affiliation of two entities to the same context or domain, even if there is no direct relation between them. For example, the relation between job and skills.

From the description above, we can define the semantic matching process as evaluating the semantic similarity and relatedness between two documents based on semantic resources, like domain ontologies and KG. In the literature, several methods are proposed to grant the best matching (resumes/Offers) based on semantic references. In what follows, we cite the most used methods in this context, and we propose a classification of those approaches based on how semantic resources and technologies are used to grant an effective matching. Therefore, we distinguish four categories: Ontology-based method, Relevance Feedback, Classification, and Knowledge graph-based methods.

3.2.1. Ontology-based method

Several works have exploit ontologies to deal with the matchmaking issues, considering ontology as a directed graph of concepts; each concept is connected to other through taxonomic relationships. We can represent this graph in several ways, for example, Description Logic (DL). Basic reasoning mechanism of DL is concepts classification, which determines the subsumption relations between the concepts. So

let the concepts represent the skills (S) where $\subseteq$ the relation over S, and the two skills $s1, s2 \in S$, when $s1 \subseteq s2$ and the s1 is a specialization of s2. It means that if an applicant possesses the skill s1, he also possesses the skill s2 that is more general by the definition.

Ontology-based methods can be broadly categorized as Edge counting approaches, Feature based approaches and Information Content based approaches.

Ontology Edge-based approaches use these relationship paths to determine the similarity score between skills from resumes and Offers. Let the path define as $P(s1, s2) = e1, e2 \ldots en$, where e_i represents the edges connecting two skills along the path. The length of the path between two concepts taken as the measure of similarity. Resumatcher [10] is a job recommender system proposed to rank job offers based on matching resume and offers using different similarity measure. A skills ontology have been proposed to match skills, where the minimum path between two concepts reflects the similarity between two skills. Authors in [29, 30], assume that having some skills imply that the applicant may have some other skills with certain probabilities. Therefore, they proposed ontology edge-based method to calculate the probability between skills using the subsumption relations.

Feature-based approaches assess the similarity between concepts as a function of their properties. They consider the degree of overlap between sets of ontological features. In [31], IT skills have been extracted from DBpedia [32] building a skills ontology, next the ontology's taxonomical hierarchy is used as the feature set. This last, derive the semantic similarity between skills using feature based measure, assuming if tow concepts are similar, than they tend to have more common ancestors subsuming them.

Content-based approaches depends on the amount of shared information between two terms, they proposed that the similarity between two concepts based on the number of common subsumes. Work in [33], exploit domain ontology to rank job offers based on extracting domain concepts from both offers and applicant, next the ontology content is used to determinate how well two concept are related.

3.2.2. Relevance feedback method

Relevance feedback is a technique adopted in searching for information that incrementally allows users to refine queries based on previous search results. For example, the user carefully checks the set of responses resulting from an initial query and then reformulates the query. In e-recruitment, the relevance feedback method compares resumes and offers, where a prototype for the relevant resume/offer has been defined as a semantic reference. However, the matching problem becomes a problem finding the most similar document to the prototype. [34] Proposes to use Relevance Feedback to help users find jobs with server logs from the jobFinder[4] site. In [35], E-Gen system presented as resumes ranking system, employing the relevance feedback technic to reproduce the judgment of the recruitment consultant. They present a prototype of an accepted profile and select a few candidate's answers from all relevant candidate answers, and then they try to find similar profiles or, at least, those that have much in common with the prototype. The prototype can be considered as metadata of the job offer and can be taken as a semantic reference for the matchmaking phase. In the same way, the authors in [36] proposed a resume ranking approach based on the inter-resume proximity measure, evaluating the lexical similarity between resumes sent by candidates and the relevant resume prototype to an offer.

3.2.3. Classification method

Other works introduce the matchmaking as a classification problem, so they aim to use semantic resources to classify the job offers and resumes into categories and match the resumes and offers that have the same category. Proactive [37] is a job recommender system that uses ontology first to classify the job information into categories and second to match offers and resumes based on the classification. More recently, work in [11] proposed to use both the job title and the required skills for the job post classification. First, the job post is pre-processed and filtered by removing noisy information. Then, a skill knowledge base is used to classify jobs and exploit an algorithm to produce weights for the

---

[4] http://www.jobfinder.com

occupational categories. Next, to match resumes and their corresponding job post, semantic resources (WordNet and YAGO3) and statistical concept-relatedness measures are used in addition to the categories of the documents to find the best matching.

3.2.4. Knowledge graph-based method

KG is a collection of interlinked data (concepts, entities) with semantic relations, presenting the data with formal semantic descriptions, which provides a framework for data integration, unification, analytics, and sharing. The semantics of the KG can enable delivering a meaningful description of the recommended items [38] based on the semantic relation between users and items in the KG. In recent works, KG has been used as a rich, structured, and related source of data that can guide linking job seekers with relevant job offers. Therefore, [39] proposed a job recommendation system based on a knowledge graph structure that uses multiple types of relations between the graph nodes. Since the nodes represent users and jobs, the multi-type links allowed them to capture and mode considerable behavioral and contextual similarities between users and jobs. The authors in [40] also presented jobs and user profiles as nodes in the knowledge graph, interlinked with relations created based on the calculated similarities. Then, the direct and transitive relations in the knowledge graph are employed to generate the job recommendation. Other research employs KG differently where entities from offers and resumes are extracted and linked with relations from KG. For example, work in [41] addressed a graph-based recommendations system with non-standardized job roles, considering the value of a candidate's skills in creating job recommendations. They created a skill graph, which they used as the principal base for the job recommendation system. The presented approach in [21] utilizes KG to extract information as a semantic graph then the matching process is based on the presented relations between entities, where the most relevant resume has a similar graph to the offer graph and more commune related entities.

4. Discussion

From the survey above, semantic approaches in the job recommendation context are based on processing the content of the documents using semantic resources to capture the semantics of documents (resumes/offers). The main phases in the job recommendation process are information extraction and matching resumes/offers.

The information extraction phase aims at extracting primary segments from documents for the matching phase. As we cited before, several methods exploit semantic technologies in this context. We categorized those methods into entities recognition, semantic annotation, and semantic graph extraction method. The common point between those approaches is the need for external resources like ontologies/KG to process, analyze the documents, and extract information. On the other hand, the difference between those approaches is related to the nature of the extracted information. In the entities recognition approach, the extracted information is introduced as separate entities, representing specific parts from the documents, such as skills. For the semantic annotation method, the extracted entities and relations are linked to their semantic description in a domain ontology or KG. The extracted information is presented in a formal format like RDF triple. Moreover, as the name refers, the semantic graph extraction method aims to link entities of text, forming a network or a graph, to present the preliminary information for the matching process. The entities recognition method can be used as preprocessing phase for the two last approaches. However, we can say that the two methods, semantic annotation and semantic graph extraction, are considered more efficient since they deliver the document content in a formal semantic structure, providing expressive, meaningful data for the matching process.

The phase of matching resumes and offers allows finding similarities between those documents and delivering a list of relevant job offers for a specific candidate and appropriate candidates for a given job post. The semantic technology proved its efficacy in this phase since we process the contents of documents, employing the semantics of the document's information to allow accurate matching results. We classify semantic match methods from literature into four main categories: ontology-based method, relevance feedback, classification, and knowledge graph-based method. Each method treats the matching problem differently, but the common point is using external semantic resources to estimate

the similarity between the documents. The ontology-based method exploits the structure and the content of a domain ontology to evaluate the similarity between the extracted entities. The problem is that this method is totally based on the ontology elements, which is maybe not rich enough to present all domain knowledge. On the other hand, the relevance feedback method is limited to specific information that mainly needs the intervention of a domain expert to identify the prototype that represents the link between the resume and job offers. Furthermore, the classification approach confined the matching problem to identifying documents with similar categories, which is ineffective in some cases, such as ranking jobs of the same category for a specific user. The KG is invented to reproduce human reasoning in linking data with meaningful relations, making it an excellent semantic matching reference for recommendation systems. However, for the e-recruitment domain, relations in KG are still general and not specific to the domain, which makes the difference from the ontology-based method that exploits ontology specific to the domain but may not be rich enough. In contrast, KG provides a rich knowledge base but is not specific to the domain and contains heterogenic data.

In summary, we can say that an external semantic source of knowledge guides all those methods to process the documents (resumes/offers) and achieve accurate recommendations. However, each method has its limitation and advantages; therefore, the uses of one of them depends on the user's needs, the type of the processed data, and the used recommendation theory. However, we can tell that a hybrid approach that takes advantage of those methods and avoids their limitations can achieve better results. Table 1 summarizes the proposed semantic methods in the literature and gives the pros and cons of each method.

Table 1 Comparison of the semantic methods

Phase	Methods	References	Pros	Cons
Information extraction	Entities recognition	[9-11]	– Eliminate noisy information. – Grant the quality of information.	– Unstructured presentation for the extracted entities.
	Semantic annotation	[14,16-18]	– Deliver semantic structured data. – Disambiguate the extracted data. – Allow inferring new knowledge and intelligent interpretation.	– Needs a rich domain Knowledge base
	Semantic graph extraction	[21,24]	– Inter-linked domain entities. – Structured data that reflect the context.	– Needs a rich domain Knowledge base.
Semantic matching	Ontology-based	[10,29-31,33]	– Allow intelligent reasoning, due to hierarchical and associative relations between concepts. – Deliver accurate results.	– Limited coverage of domain.
	Relevance feedback	[34-36]	– Use reference that reflect the judgment of an expert. – Facilitate ranking resumes/offers.	– Confine the matching phase to the syntactic similarity with the prototype.

Classification	[37,11]	– Regroup the documents into categories.	– Results with low precision.
Knowledge graph-based	[21,38-41]	– Exploit rich semantic related dataset.	– KG contain general relations and heterogenic information

5. Conclusion

A *job recommender system* is a system that automatically returns a ranked list of relevant jobs/resumes. It plays a significant role in connecting employees and employers. In this paper, we have introduced the job recommendation issue. Several works have focused on how people can find the right job and how an employer selects the best candidate; we have presented the traditional recommendation approaches and spotlight the uses of semantic technologies in different phases in the job recommendation process, like the information extraction and matching. Besides, we present a comparative study between the cited methods, munching the standard point and each method's pros and cons.

As a first observation, the semantic methods proved their efficacy in processing documents and extracting semantic information in a structured formal format. Employing semantic matching methods over the resulted information using ontologies and KG grants an accurate recommendation.

In the future, we attempt to propose a hybrid semantic approach to rank job offers for a given resume and help improve user experience in searching for the right job. First, we proposed to extract information and annotate both resume and offer with one common ontology delivering a unified presentation of both documents [42]. The next step is matching the extracted information using both domain ontology and KG to find the semantic similarity and relatedness between the resume and job offers.

References

[1] Francesco Ricci, Lior Rokach, and Bracha Shapira. Recommender systems: introduction and challenges. In *Recommender systems handbook*, pages 1–34. Springer, 2015.

[2] Freire, M. N., & de Castro, L. N. (2021). e-Recruitment recommender systems: a systematic review. Knowledge and Information Systems, 63(1), 1-20.

[3] Dhelim, S., Aung, N., Bouras, M. A., Ning, H., & Cambria, E. (2022). A survey on personality-aware recommendation systems. Artificial Intelligence Review, 55(3), 2409-2454.

[4] Shaha T Al-Otaibi and Mourad Ykhlef. A survey of job recommender systems. *International Journal of Physical Sciences*, 7(29):5127–5142, 2012.

[5] Tran, M. L., Nguyen, A. T., Nguyen, Q. D., & Huynh, T. (2017, June). A comparison study for job recommendation. In *2017 International Conference on Information and Communications (ICIC)* (pp. 199-204). IEEE.

[6] Yang, J., Han, S. C., & Poon, J. (2022). A survey on extraction of causal relations from natural language text. *Knowledge and Information Systems*, 1-26.

[7] Martinez-Rodriguez, J. L., Hogan, A., & Lopez-Arevalo, I. (2020). Information extraction meets the semantic web: a survey. *Semantic Web*, *11*(2), 255-335.

[8] Musto, C., Gemmis, M. D., Lops, P., Narducci, F., & Semeraro, G. (2022). Semantics and content-based recommendations. In Recommender systems handbook (pp. 251-298). Springer, New York, NY.

[9] Çelik, D., & Elçi, A. (2012, November). An ontology-based information extraction approach for résumés. In *Joint international conference on pervasive computing and the networked world* (pp. 165-179). Springer, Berlin, Heidelberg.

[10] Guo, S., Alamudun, F., & Hammond, T. (2016). RésuMatcher: A personalized résumé-job matching system. *Expert Systems with Applications*, *60*, 169-182.

[11] Zaroor, A., Maree, M., & Sabha, M. (2017, June). A hybrid approach to conceptual classification and ranking of resumes and their corresponding job posts. In *International Conference on Intelligent Decision Technologies* (pp. 107-119). Springer, Cham.

[12] Wahab, N., Miligy, I. M., Dodd, K., Sahota, H., Toss, M., Lu, W., ... & Minhas, F. (2022). Semantic annotation for computational pathology: Multidisciplinary experience and best practice recommendations. The Journal of Pathology: Clinical Research, 8(2), 116-128.

[13] Kiryakov, A., Popov, B., Terziev, I., Manov, D., & Ognyanoff, D. (2004). Semantic annotation, indexing, and retrieval. *Journal of Web Semantics*, *2*(1), 49-79.

[14] Yahiaoui, L., Boufaida, Z., & Prié, Y. (2006, June). Automatisation du e-recrutement dans le cadre du Web sémantique. In *IC-17èmes Journées francophones d'Ingénierie des Connaissances* (pp. 51-60).

[15] Ben Abdessalem Karaa, W., & Mhimdi, N. (2011). Using ontology for resume annotation. *International Journal of Metadata, Semantics and Ontologies*, *6*(3-4), 166-174.

[16] Ionescu, B., Ionescu, I., Florescu, V., & Tinca, A. (2012). Semantic annotation and association of web documents: a proposal for semantic modeling in the context of e-recruitment in the IT field. *Accounting and Management Information Systems*, *11*(1), 76.

[17] Bizer, C., Heese, R., Mochol, M., Oldakowski, R., Tolksdorf, R., & Eckstein, R. (2005). The impact of semantic web technologies on job recruitment processes. In *Wirtschaftsinformatik 2005* (pp. 1367-1381). Physica, Heidelberg.

[18] Ahmed Awan, M. N., Khan, S., Latif, K., & Khattak, A. M. (2019). A New Approach to Information Extraction in User-Centric E-Recruitment Systems. *Applied Sciences*, *9*(14), 2852.

[19] Zhang, Z., & Ji, H. (2021, June). Abstract meaning representation guided graph encoding and decoding for joint information extraction. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (pp. 39-49).

[20] Zhang, N., Chen, X., Xie, X., Deng, S., Tan, C., Chen, M., ... & Chen, H. (2021). Document-level relation extraction as semantic segmentation. arXiv preprint arXiv:2106.03618.

[21] Maree, M., Kmail, A. B., & Belkhatir, M. (2019). Analysis and shortcomings of e-recruitment systems: Towards a semantics-based approach addressing knowledge incompleteness and limited domain coverage. *Journal of Information Science*, *45*(6), 713-735.

[22] Snasel, V., Moravec, P., & Pokorny, J. (2005, April). WordNet ontology based model for web retrieval. In *International Workshop on Challenges in Web Information Retrieval and Integration* (pp. 220-225). IEEE.

[23] Mahdisoltani, F., Biega, J., & Suchanek, F. (2014). Yago3: A knowledge base from multilingual wikipedias. In *7th biennial conference on innovative data systems research*. CIDR Conference.

[24] Senthil Kumaran, V., & Sankar, A. (2013). Towards an automated system for intelligent screening of candidates for recruitment using ontology mapping (EXPERT). *International Journal of Metadata, Semantics and Ontologies*, *8*(1), 56-64.

[25] Lu, Y., El Helou, S., & Gillet, D. (2013, May). A recommender system for job seeking and recruiting website. In *Proceedings of the 22nd International Conference on World Wide Web* (pp. 963-966).

[26] Yi, X., Allan, J., & Croft, W. B. (2007, July). Matching resumes and jobs based on relevance models. In *Proceedings of the 30th annual international ACM SIGIR conference on Research and development in information retrieval* (pp. 809-810).

[27] Daramola, J. O., Oladipupo, O. O., & Musa, A. G. (2010). A fuzzy expert system (FES) tool for online personnel recruitments. *International Journal of Business Information Systems*, *6*(4), 444-462.

[28] Martinez-Gil, J., Paoletti, A. L., & Schewe, K. D. (2016, August). A smart approach for matching, learning and querying information from the human resources domain. In *East European Conference on Advances in Databases and Information Systems* (pp. 157-167). Springer, Cham.

[29] Rácz, G., Sali, A., & Schewe, K. D. (2016, March). Semantic matching strategies for job recruitment: A comparison of new and known approaches. In *FoIKS* (pp. 149-168). Springer, Cham.

[30] Rácz, G., Sali, A., & Schewe, K. D. (2018, May). Refining Semantic Matching for Job Recruitment: An Application of Formal Concept Analysis. In *International Symposium on Foundations of Information and Knowledge Systems* (pp. 322-339). Springer, Cham.

[31] Balachander, Y., & Moh, T. S. (2018, August). Ontology based similarity for information technology skills. In *2018 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)* (pp. 302-305). IEEE.

[32] Bizer, C., Lehmann, J., Kobilarov, G., Auer, S., Becker, C., Cyganiak, R., & Hellmann, S. (2009). Dbpedia-a crystallization point for the web of data. *Journal of web semantics*, *7*(3), 154-165.

[33] Heggo, I. A., & Abdelbaki, N. (2018, February). Hybrid information filtering engine for personalized job recommender system. In *International Conference on Advanced Machine Learning Technologies and Applications* (pp. 553-563). Springer, Cham

[34] Bradley, K., & Smyth, B. (2003). Personalized information ordering: a case study in online recruitment. In *Research and Development in Intelligent Systems XIX* (pp. 279-292). Springer, London.

[35] Kessler, R., Béchet, N., Roche, M., Torres-Moreno, J. M., & El-Bèze, M. (2012). A hybrid approach to managing job offers and candidates. *Information processing & management*, *48*(6), 1124-1135.

[36] Cabrera-Diego, L. A., El-Bèze, M., Torres-Moreno, J. M., & Durette, B. (2019). Ranking résumés automatically using only résumés: A method free of job offers. *Expert Systems with Applications*, *123*, 91-107.

[37] Lee, D. H., & Brusilovsky, P. (2007, June). Fighting information overflow with personalized comprehensive information access: A proactive job recommender. In *Third International Conference on Autonomic and Autonomous Systems (ICAS'07)* (pp. 21-21). IEEE.

[38] Han, J., Zheng, L., Xu, Y., Zhang, B., Zhuang, F., Philip, S. Y., & Zuo, W. (2019). Adaptive deep modeling of users and items using side information for recommendation. *IEEE transactions on neural networks and learning systems*, *31*(3), 737-748.

[39] Shalaby, W., AlAila, B., Korayem, M., Pournajaf, L., AlJadda, K., Quinn, S., & Zadrozny, W. (2017, December). Help me find a job: A graph-based approach for job recommendation at scale. In *2017 IEEE international conference on big data (big data)* (pp. 1544-1553). IEEE.

[40] Upadhyay, C., Abu-Rasheed, H., Weber, C., & Fathi, M. (2021, October). Explainable Job-Posting Recommendations Using Knowledge Graphs and Named Entity Recognition. In *2021 IEEE International Conference on Systems, Man, and Cybernetics (SMC)* (pp. 3291-3296). IEEE.

[41] Gugnani, A., Kasireddy, V. K. R., & Ponnalagu, K. (2018, November). Generating unified candidate skill graph for career path recommendation. In *2018 IEEE International Conference on Data Mining Workshops (ICDMW)* (pp. 328-333). IEEE.

[42] Brek, A., & Boufaida, Z. (2022). Enhancing Information Extraction Process in Job Recommendation using Semantic Technology. *International Journal of Performability Engineering*, *18*(5).