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CareProfSys : a job recommender system based on machine learning and ontology to support learners' employability at regional level

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Abstract

The inclusion of machine learning and ontology-based job recommender systems in the smart learning ecosystems may enhance the learners' employability in the regional context, by assisting learners to find jobs that match their skills and experience, and lead to a high level of professional satisfaction and high retention rates. The paper presents the *CareProfSys* job recommender system, developed by the authors, based on machine learning and ontology. The system analyses the learners' skills and interests and recommends suitable job opportunities, aligned with the regional occupational classifications. The recommendation generation mechanism is based on machine learning and ontology. The paper also presents the main further improvements in the system architecture and functionality.

Keywords: machine learning, ontology, recommender system, career development, regional occupation classification.

Introduction

In the context of smart learning ecosystems and regional development (Dascalu et al, 2017; Wen, 2020; Jeladze, Pata & Quaicoe, 2017), the need for intelligent systems to assist education and learning has constantly increased. Such intelligent systems may assure the alignment of the education and training to high dynamics of labour markets, mainly due to the technology adaption at working places and the high need for green skills and climate awareness. The discussions about the actual educational and training practices include not only the suitable infrastructures, strategies, methods, and tools, but also the environmental impact and ethical concerns related to the increased use of intelligent systems into the smart learning ecosystems (EU, 2022; Agarwal, 2023).).

The use of intelligent job recommenders may drive education and training towards green and digital economy transformation, by promoting learning that increase the environmental and climate awareness. Also, they can reduce the carbon footprint of job searching, as there is not a need any more for learners to extensively travel to physical locations for job interviews.

The use of intelligent job recommenders can also promote equally accessible quality education institutions and job opportunities through the public data sources and/or user-provided information. By providing learners with personalized and accurate job recommendations, the systems contribute to the reduction of underemployment or unemployment and, indirectly, to the social and economic development.

The authors propose an intelligent system that use public data sources and user-provided information to recommend suitable career paths based on personal interests and competencies. By providing personalized and accurate job recommendations, this system can enhance learners' employability and contribute to the economic development. Also, it recommends leaning paths for a person interested in a specific job, increasing the chance for a specific career development and for job satisfaction. The *CareProfSys* system is customized for the occupations included in the European classification of occupations (ESCO, n.d.) and its localization for the Romanian labour market, through the means of the Romanian national classification of occupations (COR, 2023).

The paper is structured as follows: after the introduction, the paper presents the findings from the literature review on the job recommendation solutions that support career guidance. In the next section, the workflow for developing job recommendations is described. The architecture of *CareProfSys* system was designed mainly considering this job recommendations workflow. In separate sections, the paper presents the *CareProfSys* system architecture and discuss the adopted solution for testing the system's APIs. In Discussion section, comments are included about the *CareProfSys* system and the next steps for further system development.

Intelligent job recommender systems for career development

Career guidance is an essential aspect of the professional career development, especially for young people who are just starting their professional journey. Identifying the most suitable career paths has become increasingly difficult for the graduates due to the globalizations of the labour markets and the huge volume of the information that should be processed (Komotar, 2019). The demand of graduates for assisting services to make the transition from studying to working life has constantly increase (Fallows & Weller, 2000).

The rapid change of skills' demands on the labour markets might also make outdated the skills acquired during higher education by the time of graduation. The study conducted by Ratiskaya and Tikhonova (2019) concludes that as employability requirements constantly evolve to address new work challenges and situations, this leads to certain discrepancies in some areas between employees' skills and the needs of the labour market. This suggests that the knowledge acquired by graduates during their higher education may become outdated by the time they complete their studies.

Research conducted by Harvard University, Carnegie Foundation and Stanford Research Centre (Jessy, 2009) concludes that 15% of job success is explained by the technical skills and knowledge itself, and 85% are based on the soft skills. Regarding the long-term job success these percentages varied from 15% to 25% for soft skills and 85 to 75% for the hard ones.

The career guidance services have been expanding in recent years due to the use of job recommender systems. The first application domain for recommender systems was the ecommerce (Schafer, Konstan & Riedl, 2014). In the education field, these systems were reported to be used from 2002, when a such system was developed for recommending educational resources and suitable learning paths (Osmar, 2002). Job recommender systems become popular systems also in the career development domain, being used by the job seekers but also by the companies in the recruitment campaigns.

An extensive literature review on job recommender systems was conducted by de Ruijt and Bhulai (2021). This work considered the literature mainly from the perspective of algorithms' fairness and generality of job recommendations. In terms of algorithms' fairness, de Ruijt and Bhulai concluded that that some of the applied algorithms lead to recommendation unfairness in terms of gender. Considering the recommendation generality, it might be limited when the job recommender systems are trained on a single dataset.

The intelligent job recommender systems may be valuable tools for the job seekers in finding appropriate career paths (Zhu et al, 2019). According to Ricci, Rokach and Shapira (2011), the recommender systems are considered as being "software tools and techniques that provide suggestions for items to be of use to a user". There are different types of recommender system, defined by adopted approaches, application domain, and the recommendation generating mechanism. According to this last classification criterium there are the following: collaborative, content-based, knowledge-based, demographic-based and reclusive based recommender systems (Mogos & Bodea, 2019).

The recommender system presented in (Liu, Dolan & Pedersen, 2009) is based on web-based emergent technologies, integrated into a recruitment portal. Skills2Job (Giabelli et al, 2021) is another example of a recommender system that uses a dataset of online job vacancies from three different countries to match the skill sets with most suitable jobs. The research conducted by Parida, KumarPatra and Mohanty (2022) focuses on the job portal websites and uses machine learning to match users' profiles with appropriate employment opportunities. The use of web-based emergent technologies and online recruitment portals makes the recommender systems more accessible and effective (George & Lal, 2019).

The machine learning algorithms are frequently used for generating the job recommendations. Hong et al. (2013) developed a system that defines three clusters of applicants (proactive, passive and moderate applicants) based on applicants' characteristics (user activity, information collection and behavior frequency) by using the k-means clustering algorithm. According to the applicant's belonging to a certain cluster, the system generates a list of recommended jobs. Mhamdi et al (2020) proposed a job recommender system that groups the job offers into clusters. If an applicant finds interesting a specific job offer, all job offers included in the same cluster are recommended to the job applicant. The same k-means clustering algorithm is used.

Several research has been conducted for identify the potential of ontology in the development of job recommender systems (Ntioudis et al, 2022; Musale et al, 2016; Koh & Chew, 2015). An interesting usage of ontology is for performing a semantic matching between job applicants' characteristics and job offers requirements (Fazel-Zarandi & Fox, 2009). Lee and Brusilovsky (2007) developed Proactive, a job recommender system that include several ontologies including several job-related metadata, such as: job type, required education, experience and geographical location, for considering the distance between job and applicant location as a criterion for generating job recommendations.

The paper presents *CareProfSys* system, that is an intelligent job recommender system based on machine learning algorithms and ontology. The machine learning model implemented in the CareProfSys system is BERT - Bidirectional Encoder Representations from Transformers (Devlin et al, 2018). The CareProfSys system's ontology was defined based on ESCO occupation framework, specific for Europe. Besides occupations, the *CareProfSys* system's ontology also contains the domains of study, thus connecting education with occupations.

The mechanism for generating job recommendations

Generating recommendations represents the main process implemented into a recommender system. How this process is designed determines the architecture of the entire system. The recommender mechanism of *CareProfSys* system executes the following steps:

1) *Collecting data about user professional profile.* User profile is the starting point for the entire recommendation generating process. Data collection includes both static and dynamic profiling. The static profile data consists of demographic information provided by the user and through various tests on user's personality, IQ, and EQ. It also contains the name, date of birth, city, and country of residence, and, optionally, desired, and undesired jobs. Dynamic profiling is based on user's Curriculum Vitae in the *Europass* format and on data published on different social media. The primary social media platform considered is LinkedIn, which typically publishes data about professionals, such as: residence, self-description, education (history, and certificates), projects, hard and soft skills, and abilities, languages' proficiency, driving license etc. Instagram and TikTok platforms were also considered. These three platforms were chosen based on survey reports issued in previous research (Stanica et al, 2022a). The combination of static and dynamic profiles provides an extended and consistent user profile, all data being integrated in a JSON format and inconsistent, misleading, or false information is identified and removed.

2) *Extracting text fragments about skills from the user profile.* The second step assures the identification of user's skills by extracting relevant user profile segment. This step is performed manually at the moment, but the recommender mechanism will be automated in future updates." by combining step b) with step c).

3) *Converting the text fragments about skills from natural language (unstructured data) to structured data*. This step assures that the various declared skills, from different data sources will be mapped into a standard set of skills. This is achieved by using Natural Language Processing (NLP) techniques to classify the description of skill into a standard skill code/structure. There are two approaches to building the NLP algorithm: the first is a traditional rule-based approach using a hand-built dictionary, and the second is based on a machine learning model, named BERT - Bidirectional Encoder Representations from Transformers (Devlin et al, 2018). The rule-based approach involves creating a dictionary of keywords found in the skill description and mapping them to the correct code. This approach is easier to implement but it has poor scalability, each time a skill is interpreted, the system goes through the entire dictionary and test the given regex for every rule. It also requires frequent dictionary updates, that make this solution unsuitable for long-term use. The second approach is based on a new machine learning model. A transformative model is a neural network which learn context, therefore learns the meaning by tracking relationships in sequential data, e.g., words in a sentence. The transformer-based approach trains a classification model for tasks, using a 2-column CSV file to provide natural language representations of skills and structured results. The first column includes the natural language representation of skill and the second one includes the structured representation. This approach requires more computing power to train the model, but it is more accurate and scalable for large datasets. After the analysis of both approaches, the second approach was chosen and implemented. The implementation involved dividing the system into two parts: the trainer, which runs locally on a computer with sufficient processing power, and the classifier, which reads the pre-trained model and applies it to the input after it has been integrated into a web service.

d) *Generating the recommendations.* To generate recommendations, the following two inputs are used:

- List of the user skills
- Ontology that contains a comprehensive list of available occupations and the required skills. Ontology implemented in the system has as reference the Romanian national classification of occupations (COR, 2023). Ontology has five levels and the classes of the first four levels have an ESCO code correspondence (Dascalu et al, 2022). Fifth level of ontology contains the occupations specific to the Romanian labor market that has not an ESCO code but are included in COR. Ontology includes all details for occupations, as included in COR, meaning the associated general activities, context of work, work style, values, skills, and knowledge a person must have for that professional position. Most of the occupations have an associate job description, that provide an additional degree of detail of the occupation description. Besides the occupations, ontology also contains the domains of study, thus connecting education with occupations.

Based on these two inputs, the recommendation algorithm executes the following two filtering tasks:

- First filtering task assures the selection of all occupations requiring a higher level of experience than that of the user. For example, if a person has only one year of experience in the industry, senior-level positions can't be recommended.

- Second filtering task selects the occupations based on the required education level. For instance, engineering positions usually require at least a bachelor's degree level of education.

After the execution of these two filtering tasks, the remaining pool of possibilities is smaller. The percentage of the number of skills that user has compared to the number of required skills is computed for each and the occupations are sorted based on these percentages and the occupation with the highest percentage is recommended.

For the next version of *CareProfSys* system, further filtering for generating recommendations will be considered, by using collaborative filtering and other machine learning algorithms. The system may use the BERT model to find the level of similarity between the current user and other users, by calculating a similarity score for each of them. Then, the system will sort the possible matches in descending order based on this score and generate recommendations for the user. Additionally, a K-means unsupervised learning model (Puspasari et al, 2021) may be applied to cluster the profiles of professions and professionals collected from social networks, and to classify the current user's profile into a cluster and provide job recommendation of all users included in that cluster.

The *CareProfSys* system architecture

To develop *CareProfSys* system with the recommendation mechanism as previously described, a web system with a layered architecture was adopted, as the architecture solution. Being a web system, the system can be accessed through any browser. The system also exposes some REST (Representational State Transfer) endpoints for other developers to build applications from the Romanian National Classification of Occupations (COR) ontology developed by the team. Figure 1 presents the architecture of *CareProfSys* system.

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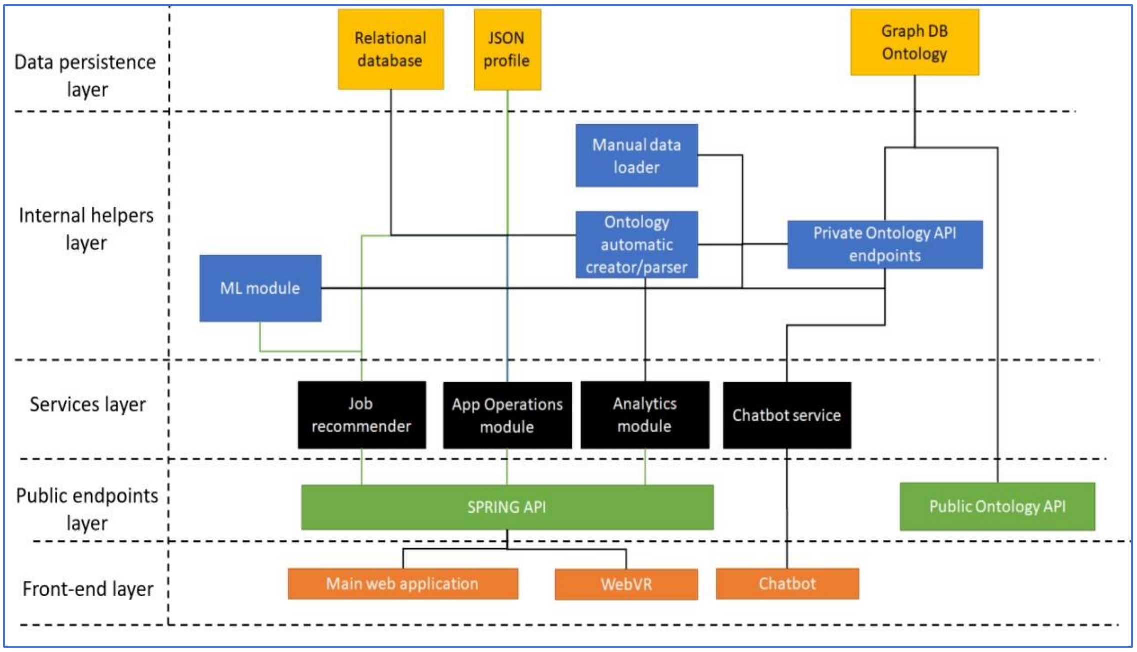

Figure 1: The *CareProfSys* system architecture

The frontend part of the system is developed by using the ReactJS framework (React, n.d.). Because the system is handling many data and passes many of this data between pages, the adopted to data handling this the use of Redux (React-Redux, n.d). For linking the frontend application with the backend services, Axios is used as a HTTP client (Axios, n.d.). The middleware for side-effects is *redux saga* because it is easy to use and easy to integrate with redux.

The backend part of the system is divided into two parts. The first part is a publicly available to other developers REST API that exploits the occupation ontology. A *rdf4j* connector connects this part to a graphDB repository that is running in a docker container (Ontotext GraphDB (n.d.). The connector is used in a spring application to run SPARQL queries on the ontology. Then, the results are converted into POJOs (Plain old java objects) that are further converted to JSON objects. The public endpoints are exposed by the controller. The second part of the backend contains the main application services. The main framework is Java Spring. Jackson is used as a JSON parser, together with several connectors for the data sources. In the second layer of the application, the following three data sources are used:

1. Occupation ontology that is accessed via the ontology exploitation API.

2. NoSQL database. The chosen database solution is Firestore Firebase in order to store the user profiles as JSON files. The connector is the official connector provided by Google.

3. SQL database – MySQL was chosen to store the application operations data, such as login details, constants, analytics, etc.

In the occupation ontology there are thousands of connections between skills, occupations, activities, descriptions, etc. With a traditional database, we would have needed complex queries to extract the relevant data, but ontology provide a simple solution for this. Figure 2 presents the occupation ontology modelled in Protégé.

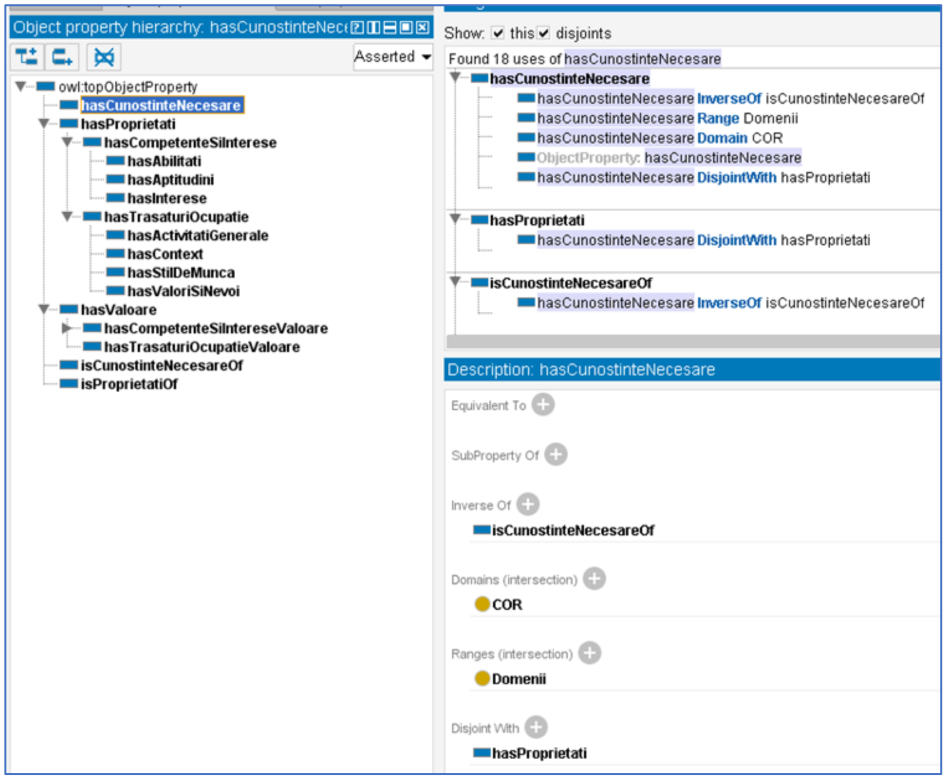

Figure 2: Relations between classes and concepts in occupation ontology. ***Source*****: (Dascalu et al, 2022)**

To illustrate the advantages of using the ontology, let us consider a user with the skills of a junior front-end developer, like JavaScript, HTML, and logical thinking. The reasoning algorithm of ontology computes the percentages of these skills relative to the required skills of each available occupation and uses this information to generate the recommendation.

The *CareProfSys* system testing and validation

During the *CareProfSys* system development each of the system components was tested. Considering the high number of APIs for testing them an efficient and robust testing solution was required. To test easier the APIs, and to provide an UI for testing, it was decided to implement Swagger UI, that is an open-source tool that allows developers to visually interact with RESTful web services and to test them using the OpenAPI (formerly known as Swagger) specification. The tool provides a web-based interface that allows users to view and interact with API documentation, as well as to submit requests to the API and view the responses in real-time. Swagger UI makes exploring and understanding the capabilities of an API easily for the developers and allows the testing and debugging of API endpoints before integrating them into the system.

Figure 3 presents the mock for testing the *CareProfSys* APIs. The provided results are as they were expected, considering a user that has both hard and soft skills that correspond to the occupation description. The user receives the recommendation of following a front-end developer career path, with a secondary option of being able to evolve in the software project management field when he/she gains enough experience.

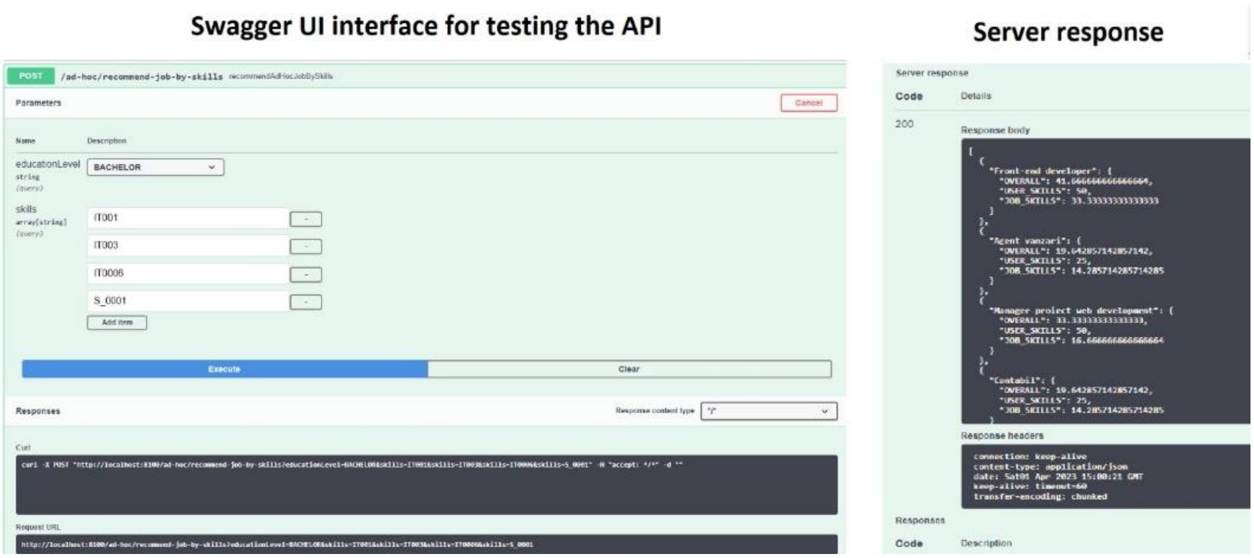

Figure 3: The mock for testing the *CareProfSys* system's APIs

The validation of the *CareProfSys* system was performed in two steps. In the first step, students looking for jobs were asked to use the system and to provide unstructured comments immediately after the recommendations were issued. The decision for collecting unstructured comments was made in order to get a high variety of information for assessing the system potential to provide interesting job recommendations. The *CareProfSys* system development team contacted the Career Guidance centre of their universities, for promoting the system, as a career service under development and for asking students to participate in the system validation. 75 students expressed their interest to get involved in the validation process and the system development team selected 60 from them, to get a good gender and specialization balance. From the selected students, 44 students used the system and send their comments. 95% of the comments were positive.

The second validation step was run after three months after the first validation step, by asking users if they applied the recommendations offered by *CareProfSys* system and which were the results. This second validation step was defined to assess the system effectiveness in terms of the job recommendations that were generated by the system. Only 17 responses were received (less than 40% of the users completing the first validation step) responded to this additional request. For this reason, the received answers were not reported as being significant for the system validation, even if most of the answers confirmed the value of the recommendations generated by *CareProfSys* system.

Discussion

It is widely accepted the need for more innovative services in career guidance of several categories of job seekers who may feel lost when it comes to selecting a career path. In response to that need, the authors have developed a web-based system that offers personalized job recommendations. With its personalized recommendations, detailed job information, and connections with professionals, *CareProfSys* system empowers individuals to make informed choices about their future, ultimately leading to better outcomes for both individuals and society (Stanica et al, 2022b).

The *CareProfSys* system is an innovative system in the career guidance as, in the first place, it offers individuals the opportunity to access detailed information about recommended jobs. They can explore job descriptions, skill requirements etc. for gaining a better understanding of different occupations. This empowers individuals to assess whether the job aligns with their interests and values, providing them with valuable insights that ultimately enable them to make informed decisions when selecting higher education institutions and specializations. In the second place, the *CareProfSys* system generate recommendations based on machine learning and ontology. As machine learning methods BERT - Bidirectional Encoder Representations from Transformers model is applied. Also, Natural Language Processing (NLP) techniques and occupation ontology are applied.

Due to the usage of these intelligent technologies, the *CareProfSys* system fits into the current trends of creating job recommendation systems, as they were identified from the literature study that was carried out by the authors. To prevent the potential generality issue, as identified by de Ruijt and Bhulai (2021), several data platforms are used by the *CareProfSys* generating mechanisms, meaning LinkedIn, Instagram and TikTok.

Conclusion

During the validation of the *CareProfSys* system, several unstructured comments were collected, that allowed the assessment of the *CareProfSys* system effectiveness. The respondents considered the job recommendations as fitting well with their characteristics, including the career preferences. The respondents didn’t report any difficulties in understanding the job recommendations provided by the system or any potential gender biases. Some of the respondents commented about the waiting time required for receiving the job recommendations. They declared that their expectation was to receive these recommendations in real-time, without any delay.

Based on the information gathered during the literature study and system validation, the following directions for further development of the *CareProfSys* system were identified:

- Improvements of the recommendation generation mechanism, by automating the entire recommendation generation and by introducing additional filtering steps, based on collaborative filtering and other machine learning algorithms.

- The use of BERT model to find the level of similarity between the current user and other users, by calculating a similarity score for each of them. Then, the system will sort the possible matches in descending order based on this score and generate recommendations for the user. Additionally, a K-means unsupervised learning model may be applied to cluster the profiles of professions and professionals collected from social networks, and to classify the current user's profile into a cluster and provide job recommendation of all users included in that cluster.

- Extending the occupation ontology, for considering additional occupation frameworks.

- Extending the actual functionality of the system with the identification of missing skills from the user’s personal profile, considering the specific occupation requirements. Based on that, suitable learning paths for filling the skills’ gaps will be recommended. With this additional recommendation function, the system will assure a holistic approach for career development and learning.

- Identification of the most frequent gaps between user's profile and competence requirements for different occupations, as included in the occupation classifications used in specific region.

These are some of the most important improvements considered for the further *CareProfSys* system development. Also, the need for more structured approaches in testing and validating the updated version of the *CareProfSys* system was identified.

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References

Agarwal SM. (2023). Go-Brown, Go-Green and smart initiatives implemented by the University of Delhi for environmental sustainability towards futuristic smart universities: Observational study. *Heliyon*, 27;9(3):e13909.

Axios (n.d.), *Getting started*. https://axios-http.com/docs/intro.

COR (2023). *Clasificarea ocupatiilor din Romania*, https://www.rubinian.com/cor_1_grupa_majora.php.

Dascalu, M.I. Bodea, C.N., Moldoveanu, A. & Dragoi, G. (2017). Towards a Smart University through the Adoption of a Social e-Learning Platform to Increase Graduates' Employability, *Innovations in Smart Learning,* Lecture Notes in Educational Technology, Springer, pp 23-28.

Dascalu, M.I., Marin, I., Nemoianu, I., Puskás, I. & Hang, A. (2022). An ontology for educational and career profiling based on the romanian occupation classification framework: description and scenarios of utilization, *The15th annual International Conference of Education, Research and Innovation,* Seville, Spain.

de Ruijt, C. & Bhulai, S. (2021). Job Recommender Systems: A Review, arXiv:2111.13576v1 [cs.IR].

Devlin, J., Chang, M-W., Lee, K. & Toutanova K. (2018). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding, arXiv preprint arXiv:1810.04805.

ESCO (n.d.). *European classification of occupations*, https://esco.ec.europa.eu/en/classification/occupation_main.

EU (2022). Council recommendation of 16 June 2022 on learning for the green transition and sustainable development, https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32022H0627(01)

Fallows, S. & Weller, G. (2000). Transition from student to employee: a work-based programme for ‘graduate apprentices’ in small to medium enterprises, *Journal of Vocational Education & Training*, 52:4, 665-685

Fazel-Zarandi, M. & Fox, M.S. (2009). Semantic matchmaking for job recruitment: An ontology-based hybrid approach. Proceedings of the 8th International Semantic Web Conference, Chantilly, VA, USA.

George, G. & Lal, A.M. (2019). Review of ontology-based recommender systems in e-learning, *Computers & Education.*

Giabelli, A., Malandi,L., Mercorio, F., Mezzanzanica, M. & Seveso, A. (2021). Skills2Job: A recommender system that encodes job offer embeddings on graph databases, *Applied Soft Computing*.

Hong, W., Zheng, S., Wang, H. & Shi, J. (2013). A Job Recommender System Based on User Clustering, *Journal of Computers*, vol. 8, no. 8, 1960-1965.

Jeladze,E., Pata, K. & Quaicoe, J.S. (2017). Factors Determining Digital Learning Ecosystem Smartness in Schools, *Interaction Design and Architecture(s) Journal - IxD&A*, N.35, pp. 32-55.

Jessy, J. (2009). Study on the Nature of Impact of Soft Skills Training Programme on the Soft Skills Development of Management Students, *Pacific Business Review*, pp. 19–27.

Koh, M.F. & Chew, Y.C. (2015). Intelligent job matching with self-learning recommendation engine. Procedia Manufacturing, 2015, 3, 1959–1965.

Komotar, M. H. (2019). Global university rankings and their impact on te internationalisation of higher education, *European Journal of Education,* pp. 299-310.

Lee, D.H. & Brusilovsky, P. (2007). Fighting information overflow with personalized comprehensive information access: A proactive job recommender, Proceedings of the Third International Conference on Autonomic and Autonomous Systems (ICAS’07), Athens, Greece.

Liu, J., Dolan, P. & Pedersen, E.R. (2009). Personalized News Recommendation Based on Click Behavior, *Intelligent user interface,* Hong Kong.

Mhamdi, D., Moulouki, R.,El Ghoumari, M. Y., Azzouazi, M. & L. Moussaid, L. (2020). Job Recommendation based on Job Profile Clustering and Job Seeker Behavior Seeker Behavior, Procedia Computer Science 175 (2020) 695–699.

Mogos, R.I. & Bodea, C.N. (2019). Recommender systems for engineering education, *Revue Roumaine des Sciences Techniques, Série Electrotechnique et Energétique,* vol. 64, issue 4, Bucarest, pp. 435–442.

Musale, D.V., Nagpure, M.K., Patil, K.S. & Sayyed, R.F. (2016). Job recommendation system using profile matching and web-crawling. International Journal of Advance Scientific Research and Engineering Trends, vol.1, issue 2, 29-34.

Ntioudis, D., Masa, P., Karakostas, A., Meditskos, G., Vrochidis, S. & Kompatsiaris, I. (2022). Ontology-Based Personalized Job Recommendation Framework for Migrants and Refugees. Big Data and Cognitive Computing, 6, 120.

Ontotext GraphDB (n.d.). Get the Best RDF Database for Knowledge Graphs. https://www.ontotext.com/products/graphdb/.

Osmar, Z. (2002). Building a recommender agent for e-learning systems, Proceedings of the International Conference on Computers in Education (ICCE'02), 55-59.

Parida, B., KumarPatra, P. & Mohanty, S. (2022). Prediction of recommendations for employment utilizing machine learning procedures and geo-area based recommender framework, *Sustainable Operations and Computers,* pp. 82-93.

Puspasari, D., Damayanti, L. L., Pramono, A. & Darmawan, A. K. (2021). Implementation K-Means Clustering Method in Job Recommendation System, *The 7th International Conference on Electrical, Electronics and Information Engineering (ICEEIE)*.

Ratiskaya, L. & Tikhonova, E. (2019). Skills and Competencies in Higher Education and Beyond, *Journal of Language and Education,* pp. 4-8.

React (n.d.). *The library for web and native user interfaces,* https://reactjs.org/

React-Redux (n.d). *Official React bindings for Redux,* https://react-redux.js.org/.

Ricci, F., Rokach, L. & Shapira, B. (2011). Introduction to Recommender Systems, *Recommender System Handbook,* Springer.

Schafer,J. B., Konstan, J. & Riedl, J. (2014). Recommender Systems in E-Commerce, https://www.researchgate.net/publication/2507550

Stanica, I., Hainagiu, S., Neagu, S., Litoiu, N. & Dascalu, M.I. (2022a). How to choose one's career? a proposal for a smart career profiler system to improve practices from romanian educational institutions, *The 15th annual International Conference of Education, Research and Innovation*, Seville, Spain.

Stanica, I., Mitrea, D. A., Bodea, C. N., Dascalu, M.I. & Hang, A. (2022b). Building relevant electronic profiling for automated career recommendations, *The 40th IBIMA (International Business Information Management Association) Conference*.

Wen, L. (2020). Construction and evaluation of a smart learning ecosystem for college English, *J. Phys.: Conf. Ser*. 1629 012035

Zhu, C., Zhu, H., Xions, H., Ding, P. & Xie, F. (2019). Recruitment Market Trend Analysis with Sequential Latent Variable Models, *ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, California, U.S.