



An Innovative Recommendation System for a Knowledge Transfer Matchmaking Platform

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Abstract. The phenomenon of aging, which has become more prevalent in our society in recent decades, has raised a number of concerns about the well-being of the elderly. Studies show that a significant percentage of retired seniors suffer from depression as a result of inactivity and a poor social environment. In order to provide seniors an opportunity to reintegrate into a healthy work environment, a knowledge transfer platform was created, with the goal of allowing seniors to share their knowledge with organizations that required the experience of a specialist. The paper presents a hybrid system that can recommend mentors for a certain assignment to companies, based on their abilities. Using AI agents, a combination of a matchmaking system and a collaborative filter calculates the similarity between the corporate profile and candidate profiles. The functionality of the system has been tested on different scenarios.

Keywords: Active Ageing · Knowledge Transfer · Recommendation System · Matchmaking System · Machine Learning · Semantic Similarity

1 Introduction

Over the centuries our society has grown as a result of human involvement, the purpose towards which this evolution tends, being that of providing an adequate level for living, regardless of ethnicity, gender or age. Based on this idea, many studies have been made, to observe and analyze the life of the elderly, considering that the standard of living has increased significantly in the last decades. The World Health Organization (WHO) states in [1] that the phenomenon of rising life expectancy would result in fast ageing populations all around the world, including in areas with a young population structure. They estimate that the category of people over 60 years will increase from 46 million in 2015 to 147 million in 2050.

One of the major concerns regarding aging is the psychological condition, depression being often met on older adults. To prevent this medical illness, many studies [2, 3] have

been made, which demonstrated how important is to offer out elderly people social support, integrating them in all aspects of society.

In order to provide this support, many projects were developed, some of them being focused on reintegrating the seniors into the work environment, giving them the opportunity to share their knowledge.

There are various on-line platforms dedicated to helping older people discover jobs that suit their needs, but the problem is that these sites follow the same basics and structures as all other job search sites. The weakness of this classic approaches consists in the fact that they don't provide an environment friendly to seniors. Besides the complicated interfaces, these sites are created to offer a normal job (full-time/part-time), neglecting the possibility of mentoring for a specific project or a single task or a system for exchange of knowledge. Furthermore, the recommendation systems for these types of sites offers recommendations to seniors, which means that seniors must choose the best alternative for them from a long list of work opportunities, making the entire process time-consuming.

The recommendation systems used for job search sites are varied and include systems like [4], where the recommendation for a job is made based on a favorite list, created by the searcher. When the list is formed, the algorithm recommends jobs that are similar with those from favorite list. Another approach [5] use convolutional Neural Network (CNN) to extract and match the words from skills section, to recommend a job. The authors of [6] used Word2Vec to calculate the similarity between a candidate for a job and a company based on different elements such as: skills, experience, designation, distance and progress.

In [7] the authors purpose a recommendation system for knowledge transfer platform, which wants to bring together the young and the older generation, the first category, benefiting from the knowledge and experience of the latter one. The recommendation system has the role to bring in contact the mentor (person who has an expertise in a domain) and mentee (person who benefits by the mentor knowledge). The suggested system is based on the history of user, one of suggested approaches being that of using machine learning algorithms to recommend a person based on previous needs of a mentee.

The WisdomOfAge platform was presented in [8], where the authors provide an excellent perspective on a very suitable architecture for senior people. The platform is developed as a knowledge transfer platform, which brings together companies and mentors from the engineering sector. In this way the companies having the possibility to work with specialists in certain domains, and the mentors having the possibility to share their experience. The WisdomOfAge motto and goal is presented on the front-end interface as in Fig. 1.

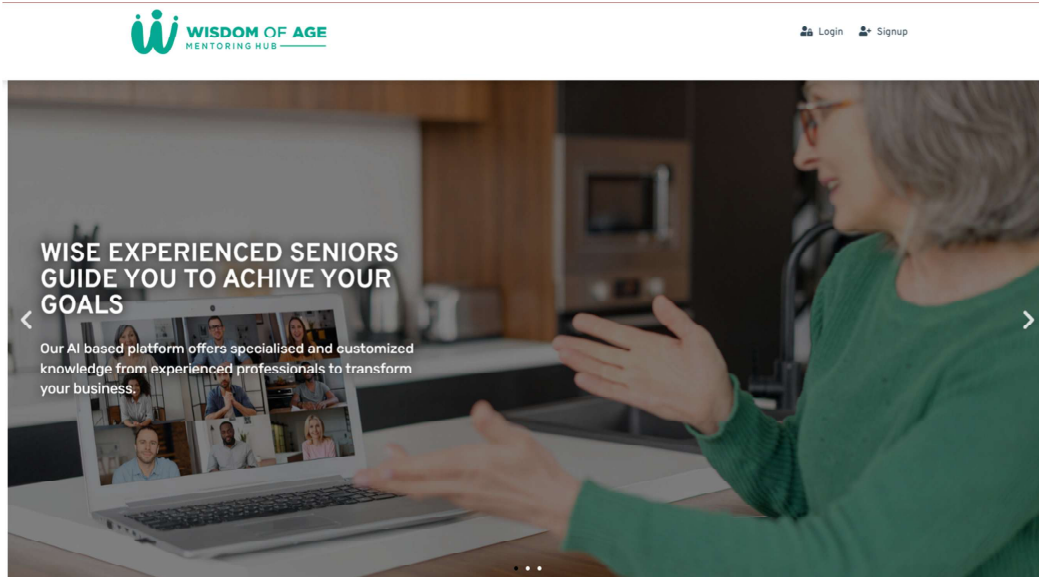


Fig. 1. Interface of WisdomOfAge platform.

The aim of this paper is to provide a hybrid system for the WisdomofAge platform, composed of a recommendation system and matchmaking system, using machine learning (ML) algorithms, to recommend a mentor (senior) to a mentee (company). This system will take into consideration aspects such as skills, descriptions, and the choices of other companies from a similar field, to recommend the best candidates for a task or a project. This approach is focused on the comfort of seniors, who can avoid the employment search, since the recommendation is for mentees, who will contact the mentor.

The paper is organized as follows: Sect. 2 makes an in-depth analysis of the existing recommendations systems, Sect. 3 illustrates the architecture of the proposed recommendation system, followed by Sect. 4 where the matchmaking system was tested based on different scenarios. Section 5 summarizes the work and presents the conclusions.

2 Critical Analysis of the Current Recommendation Algorithms

Recommendation systems are designed to offer the best option for a person based on different features like behavior, interests, or similarities with other profiles. Because these systems are developed to create recommendation based on profile specifications, they can be implemented in various domains, being often used to suggest movies or music, to help consumers on shopping sites or to recommend jobs, on jobs search websites. Considering the sector for which the recommendation is made, these systems can be approached considering three recommendation techniques.

2.1 Content Based (CB)

As can be seen in Fig. 2 Content Based (CB) recommendation is focused on the interests of the person. This type of system, like the one described in [4], identifies characteristics that are reflective of a profile and then suggests material based on those characteristics. The benefit of this method is that it is person-oriented, with suggested content based on his tastes and what that individual like or dislikes. However, these systems have the problem of requiring a large amount of data for training.

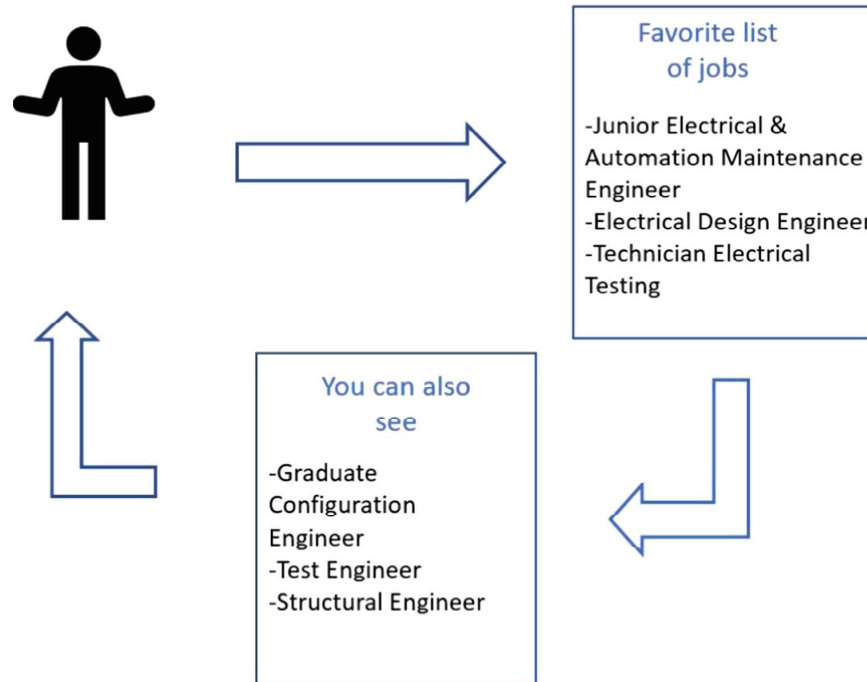


Fig. 2. Schematic representation of Content Based system

2.2 Collaborative Filter (CF)

This type of system is based on similarities between persons and their previous choices, as shown in Fig. 3. Based on the assumption that people with similar profiles have similar interests, these algorithms try to figure out what similar users might like, making recommendations based on cluster preferences, where a cluster can be a collection of people with similar wishes. An example of using collaborative filter in job search sites can be seen here [9], where the authors proposed a collaborative filter algorithm to support the recruiter in the final decision. Compared with content-based recommender, these algorithms have the advantages to be more tender, helping the users to discover a new interest. However, these algorithms present weaknesses such as the cold-start problem, which is caused by the system's inability to handle elements that were not seen during the training phase.

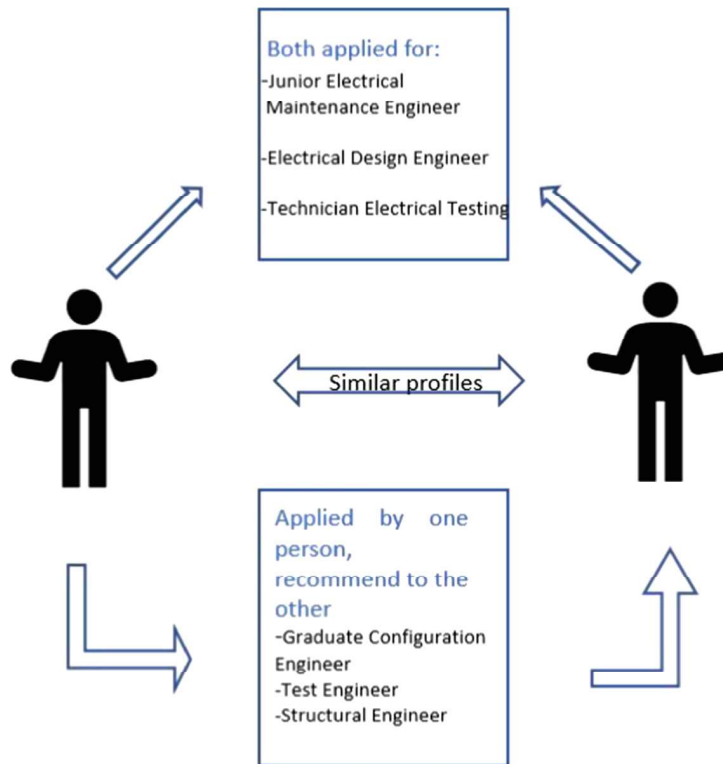


Fig. 3. Schematic representation of a Collaborative Filter

2.3 Hybrid Recommendation

Combining characteristics from both Content Based Recommender and Collaborative Filtering, Hybrid Recommender represent a viable choice for jobs search sites. Based on the different kinds of approaches, there are several types of hybrid recommenders:

- a) **Weighted:** In this configuration, the system takes outputs from both CF and CB and combine the scores to produce a single recommendation.
- b) **Cascade:** This type of hybrid recommendation system uses a system for a preliminary recommendation, and another system to adjust and resolve issues of the first result.
- c) **Switching:** The system is built to switch between systems depending on dataset in order to provide the best output.
- d) **Mixed:** This approach is ideal for extensive number of recommendations because this technique uses both CB and CF simultaneously, combining at the end the results and producing a single recommendation.
- e) **Feature combination:** In Combination Features system the collaborative system is used to provide additional feature data, the data being associated with examples and Content Based system use this augmented data to make the final prediction.
- f) **Feature augmentation:** One of the systems is used to produce a rating or a classification and this output is used in the main recommendation system.
- g) **Meta-Level:** Being very similar to feature augmentation, this technique uses a model generated by one system, as an input for the other one. The difference is the output

from first system. In the first case a learned model generates features as input for the second one, in Meta-level, a whole model is used as input [10].

3 Recommendation System Implementation

As the previous section shows, there are many techniques that can be used to build a recommender system, depending on the task. To provide a friendly platform for older people, a highly adaptive recommendation system is essential [11]. Because the traditional recommendation systems have weakness, a new approach was adopted, and a hybrid system consisting of a matchmaking system and a collaborative filter was developed.

As previously illustrated, one of the disadvantages of traditional job search sites is that candidates for a job or a task must search through a large list of positions to find the right one, this process being time consuming. Even while this method works for a certain group of individuals, it could be exhausting for an elderly person who wants to work for pleasure and does not want to waste time searching. To do so, this system will send an email to the company recommending a good applicant, and a representative person from that organization will choose and contact the individual considered to be the best fit for the task of company. As a result, the mentor is relieved of additional responsibilities.

The recommendation structure for WisdomOfAge platform have two main components: the matchmaking system and the recommendation system, shown in Fig. 4

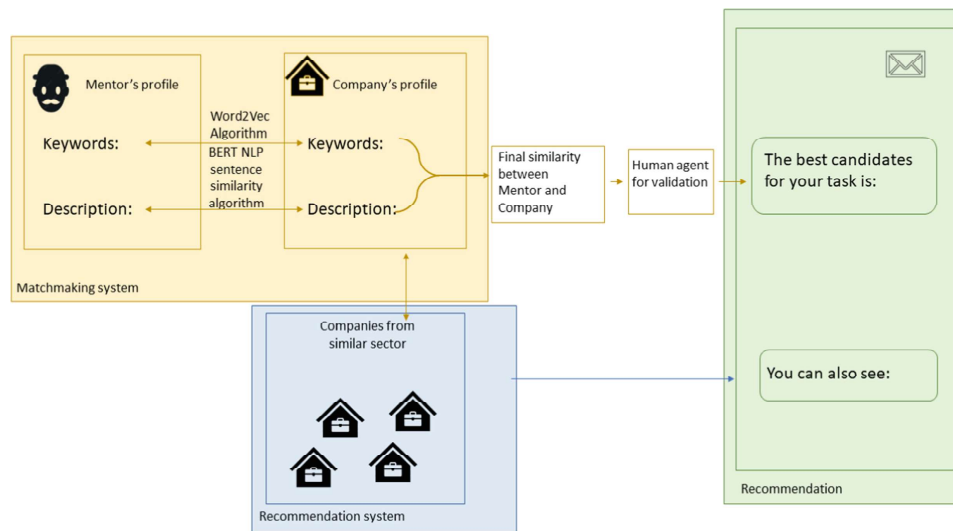


Fig. 4. Schematic representation of the hybrid system

The matchmaking system is composed of two similarity algorithms. Similarity algorithms are used to calculate the similarity between the keywords of the mentor and the keywords of the company, as well as the similarity between the description of the mentor and the description of the company. Based on that concept, the end result is a combination of these two similarities, with the highest-scoring individuals being the best prospects for the mission of the company. This result is checked by a human agent and after that, is sent to the company.

A collaborative filtering is utilized in addition to recommend mentors who were suited for companies located in the same sector, in order to gain a big and diverse viewpoint of candidates. The recommendation is based on the industry in which the company operates, as well as the ratings of the candidates who have worked with the company.

3.1 Matchmaking System

The role of the matchmaking system, as shown in the diagram from Fig. 4, is to match the company with the mentor based on the similarity degree between their profiles. To do this, two aspects were addressed: the keywords and the description. Both are required in the preliminary phase, when the mentor is setting up his profile, and the company sets its own requirements. The similarity is calculated using semantic similarity algorithms. Word2Vec algorithm has been used to calculate the similarity between keywords and the BERT NLP sentence similarity algorithm was used to calculate similarity between descriptions.

a) Word2Vec Algorithm

Although many algorithms for similarity were studied, Word2Vec algorithm turned out to be the best option for this task, being capable to compute semantic similarity between words, based on the information from training phase.

This algorithm is a trivial neural network, with just two layers, capable to reconstruct a contextual environment for words based on what was learned in training. The training phase was performed using large corpus of words, where each word receives a corresponding vector, known as word embeddings, also. The totality of these vectors produces a vector space with multiple dimensions, where each unique word represents a vector in the space. Based on the idea that words from a similar context will be placed one in the vicinity of the other, a semantic similarity between them can be calculated. A very common method to calculate the similarity between two vectors is represent by Cosine Similarity.

The cosine similarity method it's based on the known facts that $\cos(0^\circ) = 1$, $\cos(90^\circ) = 0$ and $0 \leq \cos(\theta) \leq 1$, which leads to the following formula to calculate the similarity between two vectors:

$$\cos(\theta) = \frac{A \times B}{\|A\| \times \|B\|} \quad (1)$$

The algorithm was trained using a database which contains information about engineers with different specializations, in order to obtain relevant results when the similarity between keywords is calculated. The Fig. 5 illustrates in a word cloud a representation of the text database.

the distance between these vectors is calculated using the cosine similarity to calculate the angle or the Euclidian distance to calculate the distance. The purpose of BERT in this process is to construct these vectors, also known as dense vectors, by embedding the meaning of the words in them. To do this, BERT makes use of the encoder mechanism from a Transformer (the typical structure of Transformer is composed from an encoder and a decoder). The training phase for this algorithm is composed from two stages:

- **pretraining**, where BERT learns what language and context is, using Masked Language Model (MLM), to mask random words (tokens) from a sentence, and Next Sentence Prediction (NSP), where the algorithm establishes if a sentence is in the following of another.
- **fine-tuning for a specific task** represents the step where the weights are modified, replacing the output layers of the network [16].

Based on this idea of fine-tuning in order to use BERT for a specific task, such as semantic similarity, the authors presented in [17], Sentence-BERT known as SBERT. This architecture was obtained by adding pool layers to the output of BERT, creating siamese and triplet networks, capable to calculate the semantic similarity between sentences.

For this paper, all-MiniLM-L6-v2 model was used to create proper embeddings, this model presenting these days the best performance with a short time for computation. This model is fine tuned for semantic similarity on a large dataset which contain over 1 billion of training pairs.

3.2 Recommendation System

The recommendation system is based on collaborative filters. As discussed in the previous section CF are systems based on idea that similar people have similar interests. Based on this principle, CF can be applied to a variety of activities in which human behavior and preferences provide information from which predictions can be derived.

This type of system uses a “user-item” matrix, which contains some values that indicates the preferences of user, the recommendation being based on this matrix where the values can indicate an explicit feedback (direct user ratings) or implicit feedback (indirect user behavior).

In order to implement a robust recommendations system, beside the matchmaking system, a collaborative filtering which can offer a new perspective on the list of candidates was also implemented. Considering that companies from the same sector, have similar tasks, it can be assumed that a mentor who works for a company, can work for another from the same domain, in this case the recommendation being made based on ratings given to the mentor, by the company. The approach based on explicit feedback has been chosen for this task.

The main goal for this matrix is to help in profile similarity calculation, based on rating score for every candidate. Since a company already has a good collaboration with a mentor, the system will recommend a mentor who has a similar rating score, and it is

for the same domain of activity like the previous one. To obtain a list of possible mentors based on similarities, the k-nearest neighbors (KNN) algorithm was used.

KNN Algorithm

KNN algorithm is a Machine Learn (ML) algorithm, based on supervised learning technique, which assumes that similar neighbors belong to a group. Based on this, the algorithm can assign the new data to the most similar existing group. Using cosine similarity, the distance between the target mentor and every other candidate from database has been calculated. A top X similar candidate was selected and made predictions using the average rating of top-k nearest neighbors [18]. The resemblance between companies is calculated based on their preferences for a given number of mentors, as shown in Fig. 6. A company's recommendation is based on the preferences of other companies that are similar to it.

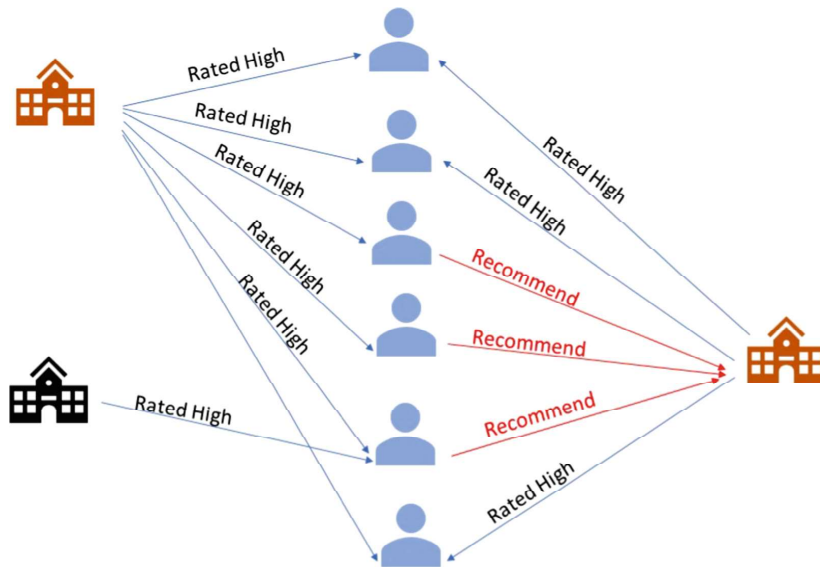


Fig. 6. A schematic representation on KNN algorithm used in Collaborative Filter

4 Testing and Validation

In order to test the system, a set of possible scenarios were elaborated because of which the matchmaking system could fail, recommending an inappropriate person for a certain task as can be seen in Table 1 and Table 2.

Table 1. Test 1 - Managing different descriptions

<p>Description of test A: In this scenario different types of descriptions ranging from short concise ones (enumeration of keywords) to very long ones (large and irrelevant descriptions for a task) have been compared.</p>	<p>Profile of the company Keywords: “electrical” Description: “You design, develop, integrate, and validate electronic circuits, primarily in the field of digital circuit technology and microprocessor systems”</p>
<p>C1: <i>Keywords:</i> “electrical, circuits” <i>Description:</i> “Mechanical Engineer with experience in Research and Development and CAD Design. I try to combine the useful with the pleasant, engineering and art, to improve the quality of life.”</p>	<p>0.7 (70% similarity between description of Candidate 1 and the de-scription of company)</p>
<p>C2: <i>Keywords:</i> “electrical, circuits” <i>Description:</i> „Experienced Electrical Engineer with a demonstrated history of working in the electrical and electronic manufacturing industry.”</p>	<p>0.76</p>
<p>C3: <i>Keywords:</i> “electrical, circuits” <i>Description:</i> “Experienced Mechanical Engineer with a demonstrated history of working in the mechanical or industrial engineering industry. Skilled in Microsoft Word, SolidWorks, Industrial Engineering, Management, and Technical Writing. Strong engineering professional with a bachelor’s degree focused on Manufacturing Engineering from UTCN”</p>	<p>0.69</p>
<p>C4: <i>Keywords:</i> “electrical, circuits” <i>Description:</i> “Experienced Civil Engineer with a demonstrated history of working in the civil engineering industry. Skilled in Tekla Structures, Timber Structures, AutoCAD, Archicad, AxisVM, Construction and Reinforced Concrete. Strong engineering professional with a master’s degree focused on Civil Engineering. “</p>	<p>0.67</p>
<p>C5: <i>Keywords:</i> “electrical, circuits” <i>Description:</i> “I enjoy creating useful and well-designed products and working in an organized manner. I can work well on my own or as part of a team. I am currently building experience as Mechanical Design Engineer, transitioning from Industrial Design. Previously I gained valuable experience in the Garment Industry, working as Sample Room Manager & Designer, then as Pattern Grader and Pattern Maker.”</p>	<p>0.70</p>
<p>Results Interpretation: According to the results of the test, Candidate 2 is the best fit for the company's needs. It's also worth noting that the similarities amongst candidates don't vary too much, which is understandable given that the descriptions all describe an engineer. In any case, if the organization need someone with electronical experience, and that person has a job description that fits the bill, that person is recommended as the ideal choice.</p>	

(continued)

Table 1. (continued)

<p>Description of test B: In this scenario were compared two types of descriptions, one with a common structure and one with a deprecated structure, where a word is repeated several times, to confuse the system.</p>	<p>Profile of the company <i>Keywords:</i> “SolidWorks, Mechanical” <i>Description:</i> “Your tasks will include design of enclosures of electronics and camera systems for car applications, requirements management, supplier contacts, and driving in further development of methodology and processes within the mechanical department”</p>
<p>C1: <i>Keywords:</i> “Design” <i>Description:</i> “I am currently building experience as Mechanical Design Engineer, transitioning from Industrial Design. Previously I gained valuable experience in the Garment Industry, working as Sample Room Manager & Designer, then as Pattern Grader and Pattern Maker”</p>	<p>0.72</p>
<p>C2: <i>Keywords:</i> “Design” <i>Description:</i> “I am mechanical engineer, working in mechanical engineering in the mechanical department of a company which produces mechanical components and mechanical engineering services.”</p>	<p>0.84</p>
<p>Results Interpretation: As can be seen the system recommend the second candidate as the best one, just because the word “mechanical” is repeated for several times. This test shown a weakness of the system, which can be resolved making the system sensitive to repeated words.</p>	
<p>Description of test C: In this scenario were compared two types of descriptions, one with a common structure and one with the entire structure formed from keyword succession.</p>	<p>Profile of the company <i>Keywords:</i> “SolidWorks, Mechanical” <i>Description:</i> “Your tasks will include design of enclosures of electronics and camera systems for car applications, requirements management, supplier contacts, and driving in further development of methodology and processes within the mechanical department”</p>
<p>C1: <i>Keywords:</i> “Design” <i>Description:</i> “Mechanical Engineer with experience in Research and Development and CAD Design.”</p>	<p>0.78</p>
<p>C2: <i>Keywords:</i> “Design” <i>Description:</i> “Skilled in AutoCAD, Microsoft Excel, Microsoft Word, PTC Creo, and Solid-Works.”</p>	<p>0.75</p>
<p>Results Interpretation: This test was thought in order to see if the system can be exploit introducing an inappropriate description (created from keywords only). The results show that Candidate 1, is considered the best choice, which means that the system can make the difference between an appropriate description and an inappropriate one.</p>	

Table 2. Test 2 - Managing different Keywords

Description of test A: In this scenario was simulated the situation when one of the candidates has one more keyword than the other candidates, but the keyword that is extra, is irrelevant for task of the company. All candidates have the same description.	Profile of the company <i>Keywords:</i> "electrical, engineer" <i>Description:</i> "Collaborate in an engineering automotive project that can address Communication networks (on-board and off-board), Electric/Electronic Architecture (functional architecture & design, conceptual E/E architecture and system integration) and Data privacy and automotive security (risk analysis and management)"
C1: <i>Keywords:</i> "Electrical, Electrical, Civil"	0.90
C2: <i>Keywords:</i> "AutoCAD, PCB"	0.57
C3: <i>Keywords:</i> "Electrical, Electrical"	0.94
C4: <i>Keywords:</i> "Electrical, Current"	0.82
C5: <i>Keywords:</i> "Voltage, Schematics"	0.72
C6: <i>Keywords:</i> "Electrical, Engineer"	0.97
Results Interpretation: According to the result of this test, a longer list of keywords, doesn't influence the similarity, just because is longest, because the system can recognize the words that are irrelevant.	
Description of test B: In this scenario was simulated the situation when one candidate has two keywords while the other only has one, but the keyword of the second candidate is identical to the keyword of company.	Profile of the company <i>Keywords:</i> "electrical, engineer" <i>Description:</i> "Collaborate in an engineering automotive project that can address Communication networks (on-board and off-board), Electric/Electronic Architecture (functional architecture & design, conceptual E/E architecture and system integration) and Data privacy and automotive security (risk analysis and management)"
C1: <i>Keywords:</i> "Electrical"	0.98
C2: <i>Keywords:</i> "Voltage, Schematics"	0.72
Results Interpretation: The result of this test reveals that many keywords in a list, even that are all relevant with the requirement of company, cannot propel a candidate if another has identical words with the company.	

5 Conclusions

Many studies have revealed that depression is one of the major problems for the elderly people, the major cause being the inactivity and the poor social life. In this context WisdomOfAge is a platform designed to provide a solution to a real challenge of our society, trying to reintegrate the elderly in a healthy social activity, like working environment. The structure of this platform was thought to be oriented for the comfort of mentor, including the recommendation system. The recommendation system was developed to recommend candidates for a task (mentors) to a company, based on a system composed from matchmaking system and collaborative filter using AI agents.

A series of trials were effectuated to verify the effectiveness of matchmaking system, analyzing both the Word2Vec and the BERT algorithm in order to calculate the similarity between a company and a mentor. As the trials reveals, Word2Vec algorithm, offers relevant values of similarities for different situations which can usually confuse a matchmaking system e.g. when a mentor introduces more words than others, although the words entered are not closely related to the company's words. Pretrained SBERT model, also presented good performance in calculating the similarity of the descriptions, even though this presents weakness when the description is perturbed with a word repeated several times.

Future work focuses on eliminating these weaknesses to provide a good experience for both company and mentor, increasing in this way the level of trust in the recommendation system and implicitly in the platform.

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