Chapter 41
An Experimental Evaluation of the Performance and Key Factors of Intelligent Recommendation System

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Abstract The implementation of recommendation systems on different websites, to offer a satisfying experience to user (related both to work and pleasure time), became a vital component for various platforms. Such a system must consider a variety of needs that are unique to the domain for which it is utilized, making its development difficult. The aim of this paper is to analyse the requirements for a recommendation system that can be implemented in applications designed act as a matchmaker between demand and supply in human resources, connecting companies with senior mentors, and to develop a system that satisfies these requirements. The proposed hybrid system is implemented in a knowledge transfer platform, dedicated to elderly people, where the recommendation is using artificial intelligence agents.

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The system has been tested on different scenarios to estimate the accuracy of the matchmaking process.

Keywords Recommendation system · Matchmaking · Semantic similarity · Machine learning

41.1 Introduction

The most well-known recommendation systems (RS) are found in e-commerce, e-learning, movie and music streaming websites, and job search websites. These platforms use recommendation algorithms, also referred to as recommendation engines, to provide recommendations to users based on their individual needs.

The systems are designed to examine a profile of user to offer an appropriate recommendation based on characteristics such as interests or similarities between people, who share related interests. RS creates suggestions utilizing a variety of methods, the most well-known of which are: Content based recommendations (CB), where the suggestions are made using the previous choices of the user; Collaborative Filtering (CF), which recommend new items based on clustering approach, where the suggestion is made to a user based on previous choices of another users with similar profiles and Hybrid Systems, which imply the combination of different systems to develop a robust framework [1].

Although recommendation systems are frequently studied for streaming or e-commerce platforms [7], where the suggestions are essentially content or purchases, these systems can also be used to assist recruiters on job platforms or to recommend an appropriate person for vocational or training platforms, where the suggestion is a person. The major challenge in this case is to build a system which can recognize the features of involved parts: the profile of company/students and the profile of candidate/mentor, in order create the best pair between them.

Because these types of recommendation systems must recommend a person suitable for a specific task, the main challenge for a system like this, is to choose why a person is more suitable than others for a task or a project. In addition, the degree of accuracy of a system used to recommend a person must be much higher than the degree of accuracy for recommendations based on products or content.

The knowledge transfer platform presented in [3], is a response to a well-known problem in Europe: reintegration of elderly people in professional activity, considering that a sedentary and aimless life, often leads toward problems like social isolation, depression, physical degradation and so on. In addition to this, the platform has the potential to respond to another problem of our society: the scarcity of people with experience in engineering. The recommendation system task is to pair a company (mentee) with a senior (mentor), considering the task of the company and the skills of the mentor.

An analysis of the system is performed based on the main characteristics and challenges specific to this type of system. The paper is structured as follows: Sect. 41.2

evaluates different architectures for recommendation systems and analyzes the characteristics for a recommendation system used on a knowledge transfer platform, Sect. 41.3 describes the proposed recommendation system, followed by the Sect. 41.4 in which testing results made on system is presented. Section 41.5 offer a perspective about future work and presents the conclusion.

41.2 Possible Architectures of Recommendation Systems

The architecture of recommendation systems used in job search websites or knowledge transfer platforms differs depending on the specific requirements of each assignment.

In [8] the authors present a recommendation system for Research and development (R&D) projects, in which companies obtain recommendations for potential researchers to collaborate on various projects. The proposed system is consisting of two parts: an offline module for selection of candidates and an online module for context-aware recommendation (recommendation based on the context of users). Another perspective for a recommendation system used in a knowledge transfer platform is described in [4], where AI agents based on Machine Learning (ML), are used to recommend a mentor to a mentee. They proposed a system based on historical data of the user, assisted by an Apriori algorithm based on extra association rules. In [2] the authors present an overview of e-Recruitment recommender systems, where the main challenges of this type of systems development, are highlighted.

An analysis of the primary characteristics of recommendation systems used in e-recruitment or mentoring platforms was conducted based on the articles mentioned above, to assess the value of these qualities for system development. For this analysis, Analytical Hierarchy Process (AHP) method was used, utilizing the following characteristics:

Matchmaking the job/task with the candidate: represents the process that achieves the matching with the available task or job, based on different characteristics.

Bidirectional process: represents the concept through which the system is built to be bidirectional, combining both the candidate/mentor and the recruiter/mentee needs.

Recommendation is made considering the attributes of candidates: refers to the need of make a recommendation based on the attributes of the candidates, in order to provide a relevant recommendation.

Large Database: refers to the amount of data that a system must be trained on in order to extract useful information.

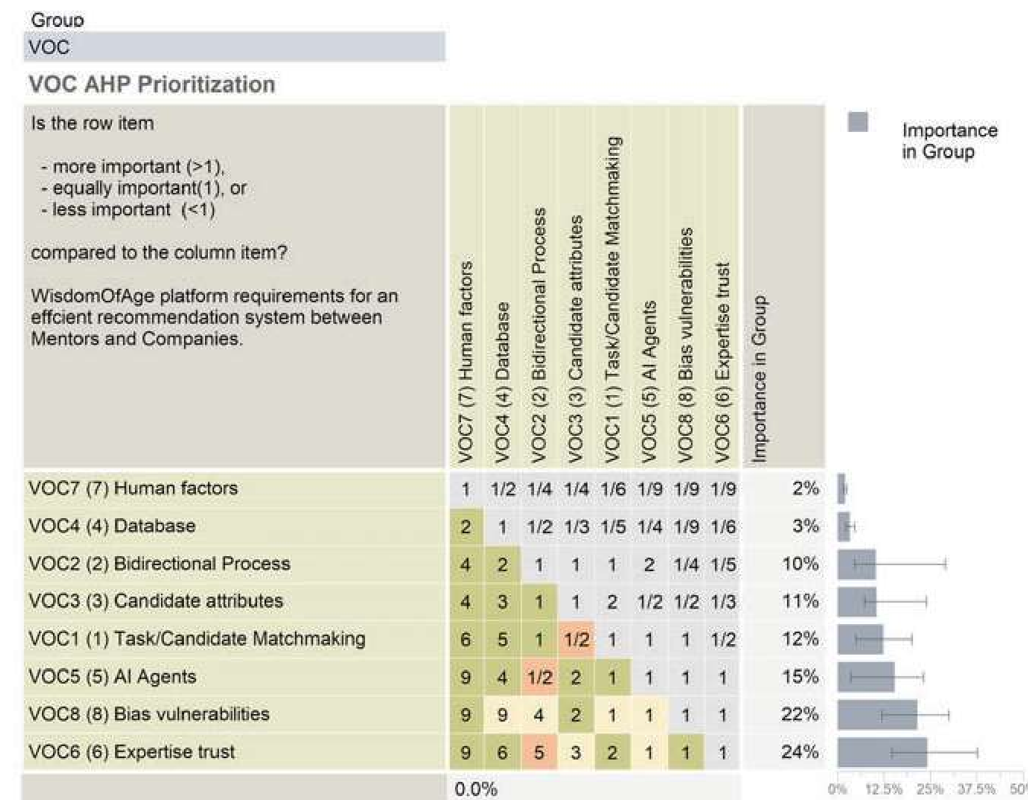
Usability of AI agents: refers to the introduction of Artificial intelligence agents in recommendation process in order to obtain valid results in a short time.

Trust in the expertise of candidates: refers to the trust in candidates and how a system can manage to provide the most reliable candidates based on an honest expertise.

The implication of human factor in the process refers to the implication of a human factor during the entire process, to verify and validate the final result.

Predisposition for bias: refer to the possibility through a system can be exploited to provide a bias for a certain candidate.

Based on AHP analysis presented in Fig. 41.1 a hybrid system for recommendations was developed, considering the trust in the mentor expertise and bias vulnerability, vital elements for platform. The AI agents are integrated throughout the system, allowing for optimal matchmaking based on candidate characteristics and company requirements.


Group

VOC

VOC AHP Prioritization

Is the row item

- more important (>1),
- equally important(1), or
- less important (<1)

compared to the column item?

WisdomOfAge platform requirements for an effcient recommendation system between Mentors and Companies.

	VOC7 (7) Human factors	VOC4 (4) Database	VOC2 (2) Bidirectional Process	VOC3 (3) Candidate attributes	VOC1 (1) Task/Candidate Matchmaking	VOC5 (5) AI Agents	VOC8 (8) Bias vulnerabilities	VOC6 (6) Expertise trust	Importance in Group
VOC7 (7) Human factors	1	1/2	1/4	1/4	1/6	1/9	1/9	1/9	2%
VOC4 (4) Database	2	1	1/2	1/3	1/5	1/4	1/9	1/6	3%
VOC2 (2) Bidirectional Process	4	2	1	1	1	2	1/4	1/5	10%
VOC3 (3) Candidate attributes	4	3	1	1	2	1/2	1/2	1/3	11%
VOC1 (1) Task/Candidate Matchmaking	6	5	1	1/2	1	1	1	1/2	12%
VOC5 (5) AI Agents	9	4	1/2	2	1	1	1	1	15%
VOC8 (8) Bias vulnerabilities	9	9	4	2	1	1	1	1	22%
VOC6 (6) Expertise trust	9	6	5	3	2	1	1	1	24%
	0.0%								

Fig. 41.1 AHP analysis for an efficient recommendation system

41.3 General Architecture of the WoA Recommendation System

The platform was designed to respond to a request very often met in present, the reintegration of elderly people in a healthy work environment, where the seniors (mentors) can share their knowledge and experience to a company (mentee).

The recommendation system is designed to offer the maximum comfort for mentors, and for this, the recommendations are made towards companies. A schematic representation of the system can be seen in Fig. 41.2.

The recommendation system architecture is based on two major components: the match-making system and the collaborative filtering.

The Matchmaking system has the role to match the mentor with the company. To make a valid match between company and candidate, a bidirectional system was developed that calculates both the semantic similarity between the keywords of the company's task and the keywords of the mentor, as well as the semantic similarity between the mentor's description and the description of the company's task. The keywords and the description for mentors and companies are required when the profiles are completed, and this information is saved in a Jason database. The process starts comparing every word from the list of keywords of the company saved in database, with every word from keywords list of every candidate, to calculate the similarity degree between them. The semantic similarity for keywords. is calculated using Word2Vec natural language processing technique. Considering that words with similar meaning are situated in close vicinity, the distance between them can be calculated, yelding a semantic similarity degree [5].

One of the major obstacles to train the Word2Vec algorithm was to find a suitable database considering that the algorithm has to calculate the semantic similarity

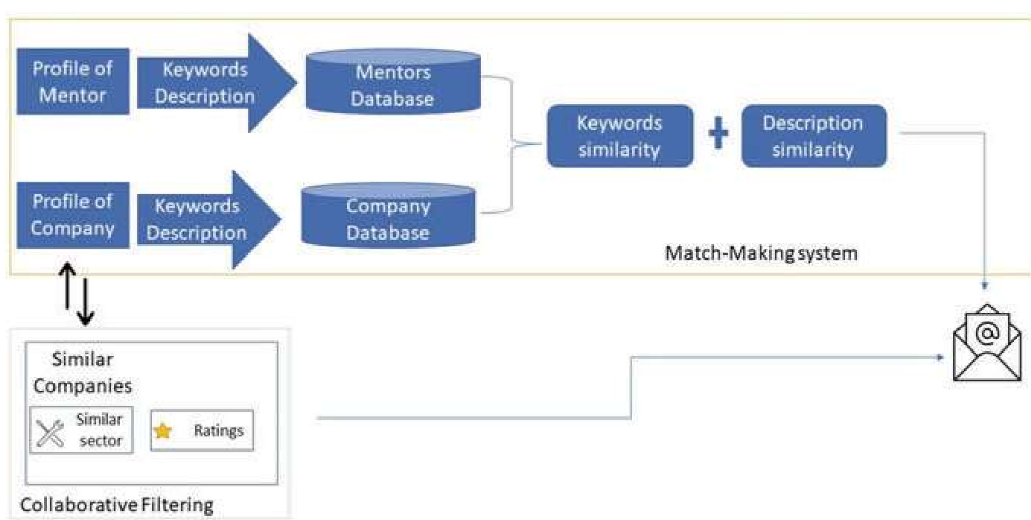


Fig. 41.2 Schematic representation of the system proposed

between specific words (eg Mechanical-Autocad), and the databases from the specialized sites are too generic. To solve this problem, was created a database composed from jobs description, in this way, the algorithm being able to learn with a suitable database. The descriptions were collected from 5 different sites (Ejobs, Linkedin, Indeed, Monster and Glassdor). The first version of database was composed from 20.000 descriptions, but has been proved to be insufficient, the algorithm presenting just 75% accuracy. After this result, to the database was added more descriptions, the final database having over 35.000 descriptions, which led to a superior accuracy, respectively 93%. Both databases were trained using the same parameters:

$$
\begin{aligned}
&Sample = 6e - 5;\\
&Window : 2,\ 3,\ 4,\ 5;\\
&Epochs : 100,\ 200,\ 300;
\end{aligned}
$$

At beginning the database was trained using window 2 and different number of epochs (started with 100 and increased to 300), at the second step the window parameter was set to 3 and the number of epochs was variated as in the previous example. The high accuracy was achieved with Sample = *6e-5,* Window = 3 and No of epochs = 300.

Based on a similar principle, the semantic similarity between descriptions is calculated using a pre-trained framework, named Bidirectional Encoder Representations from Transformers (BERT), using a Machine Learning (ML) model for natural language processing [6].

Collaborative filtering was used to complete the recommendation process. Besides the matchmaking system, which provides to the company the most suitable mentors for their task, was also introduced a collaborative filtering which makes new recommendations based on the preferences of other companies from similar domains. The system uses positive previous selections of a company (mentors who were highly evaluated by the businesses they collaborated with), to find a profile for that company. Companies with similar profiles are found, and the rating of the mentor with whom they collaborated is analyzed. In order to find the mentors with a high rating, K-Nearest Neighbor (KNN) algorithm was used. In this method, a list of mentors who were suitable for other businesses in a related sector is sent to the company in need of mentoring.

The company that wants a mentor, receives an e-mail with recommendations, the best candidates for their task being those mentors who have a high degree of similarity with the task, and the supplementary suggestions of candidates ("You can also see" section) is made based on results from collaborative filtering.

Test 1 – Order of Keywords
Description: verify if similar keywords a different order have the same similarity
Inputs:
Company-Keywords: „electrical, engineer"
Candidate 1: Keywords: "electrical, engineer"
Candidate 2: Keywords: "engineer, electrical"
Outputs: Candidate 1: 0.9323, Candidate 2: 0.9323
Observations: Candidates have the same description.
Interpretation: The system is not affected by the order of keywords.

Fig. 41.3 Representation of Test 1 with related results

Test 2 – Extra keywords
Description: verify if an extra keyword for a candidate can influences the result
Inputs:
Company-Keywords: „electrical "
Candidate 1: Keywords: "electrical, engineer"
Candidate 2: Keywords: "electrical"
Outputs: Candidate 1: 0.8312, Candidate 2: 0.8988
Observations: Candidates have the same description.
Interpretation: Because of the extra keyword (engineer), the system offers a lower similarity to the Candidate 1.

Fig. 41.4 Representation of Test 2 with related results

41.4 Experimental Evaluation of the Robust Recommendation System

In purpose of developing a reliable recommendation system for WisomOfAge platform, a series of trials were conducted. The potential exploits of the system and the ability to recommend a person with respect to the bidirectional process, were the main studied aspects. These tests are presented in Figs. 41.3, 41.4 and 41.5.

41.5 Conclusions

Recommendation systems became a very useful tool for a large range of domains, where the interests and experiences of user are important. Although these systems are common in e-commerce and streaming applications, they have become very popular in applications where the recommendation is a person, not a product. Comparing to streaming applications, where the accuracy of recommendations is not necessarily a goal, the e-recruitment platforms require extensive testing, considering the hidden character of the process. The challenges for recommendation systems used in E-learning, job sites or mentoring platforms are closely related to the bidirectional process (in which all participating parts receive a solution for their needs) and the bias exploit. This paper has examined the possibility to offer a solution for these problems,

Test 3– Detailed description

Description: verify in what degree a detailed description of mentor, influences the final result.

Inputs:

Company -Description: "In this role, the Electrical Design Engineer will complete all hardware design activities in compliance with all Project Management Office processes and procedures. He/she will be responsible for the hardware part of the automation system, including system architecture, cabinet design, network and field in system interfaces. Also, this person will work closely with the project manager and the hardware lead engineer, as well as with the supply chain assembly center."

Candidate 1: "I am an open-minded engineer who has a good ability to solve tasks that require creativity, learning, which leads me to constant progression."

Candidate 2:" Electrical Engineer with 7+ years of experience working with blue-chip companies in the consumer electronics industry, primarily focusing on implementing and debugging electro-mechanical systems. Possess excellent interpersonal abilities and a wide range of technical skills. Enjoy being part of a team, as well as managing, motivating, and training a productive team, and thrive in high-pressure and challenging working environments. "

Outputs: Candidate 1: 0.8075, Candidate 2: 0.6853.

Observations: Candidates have the same list of keywords.

Interpretation: The system showed that detailed descriptions can increase the chances of collaborating with companies. Based on this fact, the platform will recommend to users to write detailed description.

Fig. 41.5 Representation of Test 3 with related results

and a hybrid system composed of a matchmaking system and a collaborative filter was developed.

The AHP analysis effectuated to underlines the main characteristics for a system which must recommend the most suitable person for a specific task, revealed that elements such as bidirectional process, bias exploits, and implications of AI agents in recommendation process have a high significance. Considering these aspects, the recommendation system was tested based in different scenarios meant to highlight the possible weakness of the system.

Future work will concentrate on eliminating weaknesses and improving the recommendation system, introducing an algorithm able to detect discrepancy between keywords and descriptions if exists, detecting in this way possible exploits of the system or a misunderstood of the mentor/company.

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