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Integration and Recommendation System of Profiles based on Professional Social Networks

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Abstract

The aim of our investigation is to personalize bilateral recommendation of job-related proposals based on existing professional social networks. In a context where the points of view of job seekers and employers can be contradictory, our approach consists in trying to bring the both in a best possible matching. To this end, we propose an integration system that gives a minimum of credit to the users' data in order to facilitate the discovery of relevant proposals based on the users' behaviors, on the characteristics of the proposals and on possible relationships. The main contribution is the proposal of an architecture for the recommendation of profiles and job offers including social and administrative factors. The particularity of our approach lies in the freedom from the recommendation problem by using metrics proven in the literature for the estimation of similarity rates. We have used these metrics as default values to appropriate data dimensions. It emerges that, the user's behavior is exclusively responsible for the recommendations. However, the cross-analysis of randomly generated behaviors on real profiles collected on Cameroonian sites dedicated to job offers, shows the influence of the most active users. But, for requests via the search bar (interface with the script respecting the path of our architecture) the central subject remains the user. Our current work is limited by a data set that is not very representative of changing socio-economic conditions.

Keywords: *Integration system, job recommender system, social recommendations, personalized recommendations, bilateral matching problem*

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1. Introduction

In this work our reflection deals with job recommendation systems (JRS). The focus is on the imbalance between the quality of the job offers for the young graduates who face disparities between what the offers they received and their real qualifications. Similarly, the contradictory observation is that potential recruiters find that the required level is rarely achieved by most potential applicants or is not adequate for the available offers. The paradox lies in the accommodation between the requirements of the offers and the real qualifications of the profiles. Despite efforts to improve the employment situation, this remains inconsistent due to multiple enrollment procedures, under-information of the parties, but more likely due to poor customization of search results.

The problem of the mismatch between the training system and the productive system can be addressed by developing solutions that reduce these inactivity rates. In general, the more frequent the use of new technologies for different types of recruitment, the more the rate of inactivity in the labor market decreases; either by obtaining a job related to the training received, or for another whose skills must be acquired directly.

Automated profile search is still hampered by the difficulty of correctly formulating and modeling the needs expressed in natural language in an offer. Furthermore, the evaluation of personalized preferences in both directions remains dependent on the verification of beneficiary profiles by an intermediary over a reasonable period of time. At the same time, we observe through the growth of social networks, that evolving connections exist between administrative entities and between the profiles for which these entities exist.

Thus, can we reconcile personalized search, verification and validation of profiles by an intermediation that provides adequate proposals to the final actors?

Our main objective is to set up a professional profile recommendation system that includes administrative and sociological parameters. The plan of our work is, firstly, to present the fundamentals and models of recommendation and job recommendation. Next, a summary of existing systems dedicated to intermediation, in order to introduce concepts related to professional social networks, enabling a good understanding of our dataset proposal. This is followed by a comparison of similar current models. Finally, we present our proposal for a model whose architecture integrates social factors for job recommendation, and a means of verifying proposals. Finally, we begin development of our solution based on this architecture, and study its performance.

2. Fundamentals and Systems

The increase in the mass of information on the Internet has led to the need to filter the search results. Only, for the same keywords, the expected views must be different according to the specific interests; hence, the personalized search under the characteristics of a recommendation system has emerged.

2.1. Definition

The recommendation refers to a domain motivated by sorting and associating where, having an amount of information about two distinct partitions, one wishes to match according a certain level of satisfaction. A recommender system is thus a tool that suggests potentially relevant items to a user [1].

Given a set of users $U = \{u_i | i \in \{1..n\}, n \in \mathbb{N}\}$ for whom we want to make recommendations on a set of objects $O = \{o_j | j \in \{1..m\}, m \in \mathbb{N}\}$ according to their respective scores or evaluation in the form of preferences $(p_{u_i o_i})$ whose possible values are defined in a set $P = \{p_k | k \in \{1..l\}, l \in \mathbb{N}\}$. Let us respectively denote by Uo_j the subset of users having evaluated the object o_j and by Ou_i the subset of objects having been evaluated by the user u_i. We define a so-called utility function that, for user u_i, measures and then orders her most likely utilities of a set of unevaluated objects $O'u_i$ $(O'u_i = O \setminus Ou_i)$ by:

$$\begin{aligned} f : U \times O \longrightarrow f(u_i, o_j) \quad & \subset \mathbb{R}. \\ (u_i, o_j) \mapsto argmax(f(u_i, o_j)) : o_j \quad & \in O'u_i. \end{aligned} \tag{1}$$

2.2. Basic Models of Recommender

Depending on the purpose of the model (given by its name), its entries (the data of the problem) and its outputs (the recommendations), the basic functions differ. The more it is possible to combine them, the lower their respective weakness.

2.2.1. Collaborative Filtering Recommender Systems.

Here, it is a question of weighting the collaborative relationship of the evaluations provided by several users in a vast universe of objects for which the user would only visit a tiny part of them and would only give a score for an even smaller sub-part.

The idea is to impute unspecified scores because observed scores are often highly correlated between different users and items.

Based on this similarity, imputation of missing test labels is made by inferences on incompletely specified values [2].

2.2.2. Content-Based Recommender Systems.

Descriptive attributes of the elements are used hence the term content in the sense that user ratings and behavior are combined with the content information available in the elements [3].

For this method, it is assumed that users will appreciate in the future what they have already appreciated in the past. For this method, it is assumed that users will appreciate in the future what they have already appreciated in the past. The recommendation is thus directly correlated to the user's behavior in the sense that, if only one type of item is of interest, then only similar items will be proposed at the risk of losing diversity.

2.2.3. Knowledge-Based Recommender Systems.

Their usefulness lies in the context of items that are rarely visited and, therefore, have little information available for the recommendation process. This situation is common to cold start problems. The work of [4] is a good example where experts assist in evaluating knowledge criteria or thesauri for training recommendation personalization.

Here, thesauri are used as facets for the description of offers and profiles.

Based on knowledge, the recommendation process is performed on the basis of similarities between user preferences and item descriptions, or the use of constraints specifying these preferences. It is further facilitated by the use of knowledge bases (rules and similarity functions) to be used during the retrieval process.

2.2.4. Demographic Recommender Systems.

It is about recommendations based on user demographic profiles. Sociodemographic attributes such as age, gender, occupation, education, and housing are used with the assumption that recommendations should be generated for different areas. An example is that of [5] who in a context of MOOCs (Massive Open Online Courses) propose to recommend to each learner in need, a personalized list of 'Learner Leaders' who can accompany their distance learning process. Demographic recommender systems make collaborative proposals based on user demographic profiles, including managing bottlenecks between the most requested points.

Demographic recommender systems make collaborative proposals based on user demographic profiles, including managing bottlenecks between the most requested points.

2.2.5. Hybrid Recommender Systems.

In cases where consistent and diverse amounts of data are available, different recommendation models can be used independently and compared to select the best one. Another possibility is to combine them by their different positive aspects to increase the efficiency or the satisfaction of the user and at the same time, to decrease or fill their negative aspects. An example of a well-generalized operation is [6]:

The data storage module stores the input data, including historical data and notations. The preprocessed data is put into the database to be read in the higher-level modules. The prediction module calculates the prediction scores for the notes.

2.3. Systems and Methods in JRS

The level of accuracy required in such systems must be at least equal to the criteria derived from recruitment domain experts. This will help to increase the level of the accuracy matching.

For **Collaborate filtering JRS**, by identification with each of the two philosophies (User-Based and Element-Based) associated with this method, in memory-based collaborative filtering (CF) the similarity function uses a k-nearest neighbor (KNN) approach so that for a user u, it is found to have k similar users (user-based CF), or it is found to have k profiles that are neighboring in features to those that u has already liked (feature-based CF) [7].

For **Content-based JRS**, we use a semantic similarity measure between the user's profile and the set of vacancies, by estimating their respective relevance for the applicant [8]. For example, of [9] proposed, as a method, the segmentation of CV (Curriculum Vitae) into sections ordered by content, for the extraction of terms representing the skills.

For **Knowledge-based JRS**, we thus understand the direct but implicit link between offers and profiles by the use of ontologies or domain-specific knowledge bases previously identified and classified to serve as a reference for comparison. In the work of [10], in a "Skill-Based Resume Classification Module" of their architecture, each skill is exploited sequentially so as to enrich a knowledge base of skills that will later serve as an ordered list of referential categories when ranking applications.

For **Hybrid JRS**, it is a matter of combining several models into a single recommendation system. Furthermore, the hybridization gives rise to two other categories of sub-models: those known as monolithic and those known as ensembles. An example of the monolithic ones is proposed [11] in a job posting SR for a career oriented social network that consists of a Case-Based Reasoning system (CBR) and an argumentation framework, based on a Multi-Agent System (MAS) architecture.

2.4. Review of the literature on techniques in JRS

This sub-section discusses in chronological order the problems, solutions, goals, methods, results, and limitations of work based on job referral methods and systems.

2.4.1. Works based on Systems and Methods in JRS.

This work starts with collaborative filtering with [12, 13] followed by companies and academics in the development of other methods for problems filtering generated by the growth of the web.

Rating Prediction Based Job Recommendation Service for College Students: Starting from a context of ever-changing employer requirements, [14] address the cold-start problem for recommending new graduates to appropriate positions through a score prediction mechanism based on two-way company-seeker employment notifications. Only, this research has mainly studied the job recommendation from the student's point of view and as they say, it would deserve to be deepened in future works to save simultaneously the efforts of students and employers.

A combined representation learning approach for better job and skill recommendation: Through a different lens, [15] present the difficulty of developing an effective, long-term employment transition plan due to the highly dynamic nature of the labor market. Only, a limitation of their learning framework is reduced to the representation of jobs and skills available in the input graphs and thus, a perpetual recycling of representation of new entities is necessary. But their perspective is the development of an inductive learning framework.

Employment Recommendation System using Matching, Collaborative Filtering and Content Based Recommendation: Another approach is that of [16] who pose the problem for companies to recruit the right talent given the high volume of applicants. The challenge was to predict which job offers a user would interact with. Their process takes TSV files as input for analysis and transformation into a matrix through collaborative filtering. They then apply different machine learning algorithms on the matrix to find the most appropriate job for each user based on their analysis.

Hierarchical approach to extracting skills from PDF (*Approche hiérarchique d'extraction des compétences dans des CVs en format PDF*): The focus is on a framework of skills extraction in CVs or skill-gap, [9] propose an approach for automatic association between extracted skills and those required by an organization. Their contributions are summarized in the steps of their method. Nevertheless, their experiments showed an improvement in block identification accuracy of more than 10%, compared to a state-of-art model with a multi-label skill prediction capable of retrieving a 90.5% accurate skill list and 92.3% recall.

Towards a recommendation system for expert profiles in the process industry (*Vers un système de recommandation de profils experts dans l'industrie des procédés*): Here the main focus is on companies struggling to correctly modeling the needs expressed in natural language in a job offer for the recruitment of experts [17] presents an architecture of a system of recommendation of candidates with an important recall linked to profiles.

In their study, they reveal and solve barriers to the design of their system while measurably defining the fundamental concepts of recruitment.

2.4.2. Job Recommender Plateforms.

Table 1 presents a global vision of these few works for a better appreciation in the aim of the integration of professional profiles.

Notable contributions are the effective consideration of location; automatic detection of the universe of the offer; the weighting of the experience and the duration of the offer issue, so as not to propose profiles with too old experience.

[22] builds a "Web Recommendation System for Job Search and Recruitment" called Skillake. The aim is to reduce the time it takes to match job-seeker profiles with job offers (through hybridization adapted to the cold-start problem) and guarantee scalable performance, except that building the model is costly in terms of time and resources.

2.5. Concepts and Notions

For each user, a profile often subject to a comprehensive review of information is formed explicitly or not. The aim here is to provide an overview of the main concepts, platforms and methods for capitalizing on them.

2.5.1. E-recruitment.

Everything starts with a recruiter who issues, through various channels, a need described in a job offer. Then, through the response channels indicated in the offer, each candidate wishing to meet the need, will provide a CV as a confirmation of interest. Next, several recruiters may have similar needs, giving candidates the opportunity; before applying, to learn about the institutions that the recruiters represent in order to compare them and judge which ones would best meet their expectations.

2.5.2. Competency Modeling: Integration.

For each required skill, one or more missions are associated with a well-defined professional situation in terms of activities and/or requirements. This example borrowed from [23] will serve as a basis for the modeling of competences in our profile integration system. We retain from their contribution a static, general and still relevant view of the competence model.

These schemes are respectively specific to the actors for whom they integrate acquired and required skills that mobilize a set of resources and knowledge.

2.5.3. Intermediation.

According to [24] it consists by an intermediary entity, to fluidify this search and to improve its effectiveness with the aim of optimizing the costs of research by the preliminary collection of information. The intermediary would be in charge of the validation of the proposed profiles and therefore, must answer the questions of time, precision and method to a potential employer with the aim of finding compromises that

Table 1. Comparative summary of some works on JRS Platforms

N	System [Authors]	Approach & architecture	Problem :: Solution	Advantages :: Contribution	Limitations :: Disadvantages
1	CASPER: [18]	Hybrid (CB and CF) : CASPER ACF - CASPER PCR	Imprecision of searches due to poor specification of queries :: personalized search based on similarity, and a query-free collaborative filtering recommendation technique.	Their ACF combines server-side profiling and search engine :: Their PCR uses a similarity-based retrieval engine and a personalization engine based on the content of individual user histories.	CBR does not customize the individual search; PCR stores and manipulates profiles on the client side.
2	Bilateral: [19]	Hybrid (CB and CF): CV-Recommender; - Job Recommender	Matching people to jobs :: treat individual preferences as a combination of preference factors and recommendations to candidates based on their preferences, also based on previous preference scores.	The person-job match does not consider both the need supply and demand-capacity perspectives. :: Solution in search of a binary match optimally on a subset of possible matches.	—
3	Proactive: [20]	Hybrid (CB and Knowledge-based)	information overload :: development of personalized information retrieval technology based on the exact the exact needs of the user.	Cultivates user confidence through the feeling of control over the choice of these preferences; :: helping the user to locate a good portion of relevant items.	—
4	Cerebra [21]	Hybrid (CB and Knowledge-based)	Improve the computerized recruitment process for managers and professionals :: proposal of matching algorithms after the extraction of useful information, the search of profiles and the classification of results.	Improved processing of profile information from social media in predicting the success of a candidate in a position :: taking into account the location and automatic detection of the offer universe.	Does not take into account the feedback from job seekers :: Forced the recruiter to reformulate his need in case of dissatisfaction.

are beneficial to both parties. Hence the precision of reciprocal relevance is important.

2.5.4. Social Network and Social recommendations.

The combination of social network and social recommendation aims at weighting virtual links based on multilateral interactions between social entities. Their functional uses distinguish those called personal from those called professional by the seriousness to establish then to widen a community. Connecting to a professional ecosystem is now simpler and more relevant thanks to social media. But their use can be diverted giving the fact that "meaning must precede action" [25].

According to [26], the user preference influenced by socially connected contacts. The social recommendation is twofold; the one in which online social relations are used as additional inputs to an existing recommendation engine and the other broad, which refers to any recommendation system targeting social media domains.

Still, the basis remains a collaborative filtering based on users [27] where the use of the social circle replaces the calculation of the neighborhood. The major contribution is the reduction of the scaling problem. The difficulty arises in the calculation of the degrees of confidence on the parities with a user for whom we identify those who are closest to him for recommendations on the most popular items within the identified subgroup.

2.5.5. Evaluation of relevance through.

Normally, evaluations are subject to quantifiable results over periods of practice based on resulting professional goals and social ties ([3]), These evaluations are outside the scope of our work although very relevant if we deviate to pursue the work of [9] from an ontological point of view in the hierarchical extraction of information from a CV. It is always with caution that the intermediary will estimate a theoretical level or behavior. But with conviction that he will do so for practical skills focusing on the preferences of the employer first and those of the job seeker by prioritizing the location and salary at the second position.

2.5.6. Some Metrics of evaluation.

The evaluation may concern the prediction phase and/or the recommendation phase. Our case is that of an evaluation in the form of a user case study, where users only check the lists of recommended proposals without giving actual explicit scores.

In the literature, the accuracy measurement of the recommendation engine is the subject of the most known metrics are precision, recall.

Generally, metrics for prediction are *Mean Absolute Error* (MAE), *Mean Absolute Scaled Error* (MASE),*Mean Square Error* (MSE), *Root Mean Square Error* (RMSE), *Weighted Absolute Percentage Error* (WAPE), *Mean Absolute Percentage Error* (MAPE),...

Specifically for recommendation, the measurement are *Hit Rate* (HR), *Average Reciprocal Hit Rate* (ARHR), *Cumulative Hit Rate* (cHR), *Rating Hit Rate* (rHR), *Novelty*, *Diversity*,*Normalised Discounted Cumulative Gain* (NDCG),*Mean Reciprocal Rank* (MRR), *Intra-list Similarity* (ILS).

2.5.7. Similarity and Metrics of Similarity.

In chronological order, Table 2 presents the most common *Ensemblists* and *Ontological* metrics used to assign a **digital peas** to text data in **a well defined context**.

Table 2. Summary of distances or metrics to use according to the type of variable to be compared

N	Constraint	Ref. JRS	General uses in JRS
1	Sørensen-Dice (Ensemblist)	[28]	- Comparison of sets of variable size (like a work schedule in an offer)
2	Jaccard (Ensemblists): A and B have the same size	[14] [29]	- Comparison of statistical test samples; - similarity score between two objects
3	Tversky (Ensemblists)	[30]	- In the categorization of data
4	Cosine (Ensemblist)	[30] [26] [31]	- search for information (by comparison); - creation of links between entities of the same nature
5	Tf-Idf (Ontological)	[11] [28] [32]	- In the search for information (text mining)

3. Proposed Integration, Architecture and Implementation

This part attempts a general modeling of the job-specific recommendation system. We give an overview of the architecture of our approach and finally we propose the procedure for incorporating our solution.

3.1. Integration and Recommendation Model

This is the control of a number of requirements related to the nature of the insertion of a profile in the database. This prior validation, more relevant the qualities of a proposal for the process of routing between the interested parties. This expectation is also valid for the entities that will be neighboring or will have to depend on the behavior of the new one. In parallel to our modelling approach, if all the entities are viable from the outset, their level of reliability must serve as a means of sorting out their effectiveness.

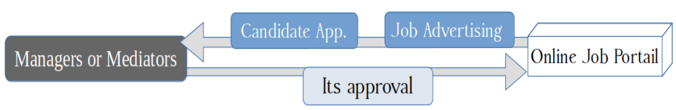


Figure 1. Proposed integration logic.

3.1.1. Data Acquisition.

In order to have personalized results that can be generalized to various sectors of activity, we implement a minimal information gathering system that respects the described requirements. We provide the justification of the collection of new data for our study. (Table 3 shows the intrinsic attributes of a good dataset according to the Dataset Definition Standard (DDS) [33]).

Table 3. Contexts, qualities, and shortcomings in recent work on JRS.

N	Contexts	Qualities	Defaults
1	Text processing	Representativeness, Completeness	Social links
2	One-way matches	Reliability	User notes
3	Bidirectional matches	Consistency	User similarities
4		Unintentional bias, Traceability	Similarities proposals

As a guideline, the criteria in Table 3 are the primary evaluators of recommending systems. Table 4 summarizes our observations and then opens up avenues for contribution.

3.1.2. Modeling of the problem.

Although we know that each offer and application is unique, there are no real rules for structuring them. Nevertheless, our approach starts from a set of forms containung mandatory or optional type. For each offer (respectively each CV), the theoretical framework comes down to maximizing its matching rate with its list of CVs (respectively offer) to be recommended while respecting the constraints of confidence and preferences.

Drawing on [34] for whom ***a recommendation problem involves***:

1. an overall objective governing selection and ranking: a set of actions to be optimized;
2. a set of available actions focused on the presentation of the recommended items and;
3. a timeframe for optimization.

3.1.3. Characterization on sets and manipulations.

$\forall u \in O_u$, $u = \{a_i : i, j \in \{1..n\}, i \neq j \Rightarrow a_i \neq a_j\}$, with a_i the i^{th} attribute of u.

Then, any similarity is defined in terms of a group of attributes.

We will therefore posit $u = [A_{i'}]_{i' \in \{1..m\}}$ with $A_{i'} = [a_{i''}]_{i'' \in \{1..m_{i'}\}}$, with $A_{i'}$ an i^{th} group of particular attributes (numerical, alphabetical, objects - dimensions) and $a_{i''}$, its i^{th} attribute.

This rewriting is necessary so that $i', j' \in \{1..m\}$, $i' \neq j' not \Rightarrow (A_{i'} \cap A_{j'} = \emptyset)$.

Because several similarity algorithms can use attributes in common.

For collaborative filtering (User (u_1, u_2), Proposal (p_1, p_2) and User-Proposal (u_i, p_j)), whatever u_1 and $u_2 \in O_u$,

$$S_{A_{i'}}(u_1, u_2) = \sum_{i'' \in \{1..m_{i'}\}} w_{i''} \times sim_{A_{i'}}(u_1.a_{i''}, u_2.a_{i''}) \quad (2)$$

with $w_{i''}$ the quantification of the importance given to the attribute $a_{i''}$ by u_1 and u_2.

Finally, the final similarity would be:

$$S(u_1, u_2) = \sum_{i'=1}^{m} w_{i'}.S_{A_{i'}}(u_1, u_2). \quad (3)$$

We note that the social similarity u_1, u_2 simply takes a social dimension A_s and the set $N_{u_1 u_2} : S_{A_s}(u_1, u_2)$.

Constraints related to historical variables (dates and identifiers):

It is the follow-up of each object: *traceability + identity*

1. An index for the formalism, is the identifier for the manipulations of each object;
2. Each profile has its value increased for each identifier of confirmation of its information;

Table 4. Current Kaggle datasets of major studies on Job Recommender Systems: qualities and shortcomings compared to ours.

N	Dataset	C_1-C_2-C_3-C_4	Q_1-Q_2-Q_3-Q_4	D_1-D_2-D_3-D_4
1	By **DIAB: jobs_data.csv(1.51 MB)** Command: >_kaggle kernels output diab91/job-recommender-system -p /path/to/ dest	C_1 : NLP for feature extraction	Q_1, Q_2, Q_3	D_1, D_2, D_4: CB
2	By **Tondji Lionel: ALL_Offers.csv(41.14 MB)**	C_1: Match a job type with its salary and sector.	Q_1, Q_3, Q_4	D_1, D_2, D_3 : CF
3	By **Tushar Sarkar: Modified.csv(4.66 MB)** Command: >_kaggle kernels output tusharsarkarit-job-recommendation -p pathtodest	C_1: match the qualities required to the qualities supposedly; C_2: profiles to offers	Q_2, Q_3, Q_4	$D_1, D_3, D_4 : CB$
4	By **Sidhant: Recommendations.csv(106.04 kB)** Command: >_kaggle kernels output thedocsit-job-recommendation -p pathtodest	C_2: From profiles to offers	Q_2, Q_3	D_1, D_2, D_3
5	By **Nishi Paul: naukri_com-job_sample.csv(52.26 MB)** Command: >_kaggle kernels output nishi216job-recommend-hands-on -p pathtodest	C_3: Bidirectional	Q_1, Q_2	D_1, D_2 : CB, CF
6	By **Wei Chun Chang: job_skills.csv(1.88 MB)** Command: >_kaggle kernels output justjun0321job-recommendation-find-you-job-at-google -p pathtodest	C_2, C_3	Q_1, Q_2, Q_3, Q_4	$D_1 D_4$: CB, CK
7	By **kandi jagadish: Combined_Jobs_Final.csv (158.59 MB)**	C_1, C_2, C_3 : using NLTK helping the applicants to choose thier preferred job	Q_1, Q_3, Q_4	D_1: CB, CF

3. the profiles recorded by the $User_0$ must be better classified than those of the $Manager_0$.

We primarily maximize satisfaction (user utility), observable by decreasing search effort through the user preference prediction measure.

Let be two groups of users with a total sum of m+m′ and, all identified by a single profile directly or indirectly associated with several offers (Figure 2). Let's look for the recommendation that would maximize a user's satisfaction (elicit "apply" or "invite" behavior).

Users: $\|\{Js : u.(type = Js)\}\| = m$ and $\|\{e : u.(type = E)\}\| = m'$;

Propositions: $\|\{p : p \in P.(u.(type = Js)\}\| = m$ and $\|\{o : o \in P.(u.(type = E))\}\| = m''$;

$Where : m, m', m'' \in \mathbb{N}\ ;\ m'' = \sum_{j=1}^{m'} \sum_{k=1}^{m'_j} \|\{e_j.o_{jk}\}\|$.

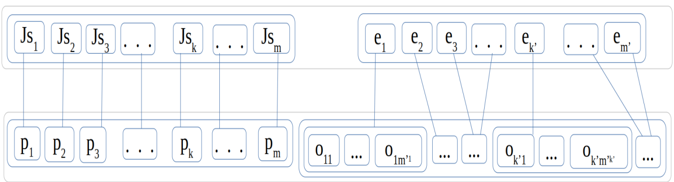


Figure 2. Overview of profile-application Js → P and profile-offer E → O relations.

Note that all the following operations are symmetrically valid for a job offerer.

Let q a Job seeker with profile Js_q. Let KW_q a set of keyworks research of q structured as:

$$\begin{aligned} KW_q &= Js_q.(\{request_q\}_l) \\ &= \{\cup_{i \in \{req_1..req_l\}} w_{l_i} : w_{l_i} \in \cup\{clean(request_q)\}_l\} \end{aligned} \tag{4}$$

and where

$clean(request_q) = steamm(lemm(request_q))$;

w_{l_i} is l^{th} keyword keep at i^{th} research.

With $n_{mm'm'_{m'}}$: the rating of the user m on the m' offer of the $m'_{m'}$ employer.

The main similarities are:

1. **the similarity of its profile with a set of searcher profiles** aming at finding users who would rate the same as the latter;
2. **the similarity of his application with those of a set of researchers** aiming at finding users who would receive similar ratings for the same dealers.

Let us note Z_1 the intersection between the results of Sim_1 and Sim_2 ($Z_1 = X \cap Y$).

The following manipulations take this into account by the following relation:

$$\forall Js_{k'} \in Z_1 \Rightarrow$$
$$Sim(Js_q, Js_{k'}) += (Max(X \setminus Z_1).Sim(Js_q) + min(Z_1).Sim(Js_q)) \quad (5)$$

3. **Its similarity with a set of supplier profiles** aming at finding the offerers who, from the start, have offers that might interest him;
4. **The similarity of his application with the requirements of a set of offers** aming at finding the ones he is likely to like or even apply for.

Let us note Z_2 intersection between the results of Sim_3 and Sim_4 ($Z_2 = X \cap Y$). As before, the following relation is taken into account:

$$\forall e_{k'} \in Z_2 \Rightarrow$$
$$Sim(e_q, e_{k'}) += (Max(X \setminus Z_2).Sim(e_q) + min(Z_2).Sim(e_q)) \quad (6)$$

In real life, it is not always true that users with similar characteristics are recommended the same proposals. In addition to $SSim_1$ and Sim_2, we model the notion of social network so that user can appreciate more importantly the proposals consulted by those he has directly or indirectly chosen to link to.

The best ratings of Z_3 users not seen by Js_q are increased by a certain priority in the ranking.

For a job seeker, what follows is to rank in decreasing order a number of offers related to the sets Z_1, Z_2 and Z_3.

We underline the fact that these operations are symmetrically performed for a recruiter.

3.2. proposed architecture

Our approach finds its singularity as a meta-model of a cascade hybridization. Indeed, it is a commutative model on time-based collaborative filtering, followed by a first fusion by weighting to the content-based one and finally, a second fusion with the filtering based on social connections, to enrich and refine the list of proposals.

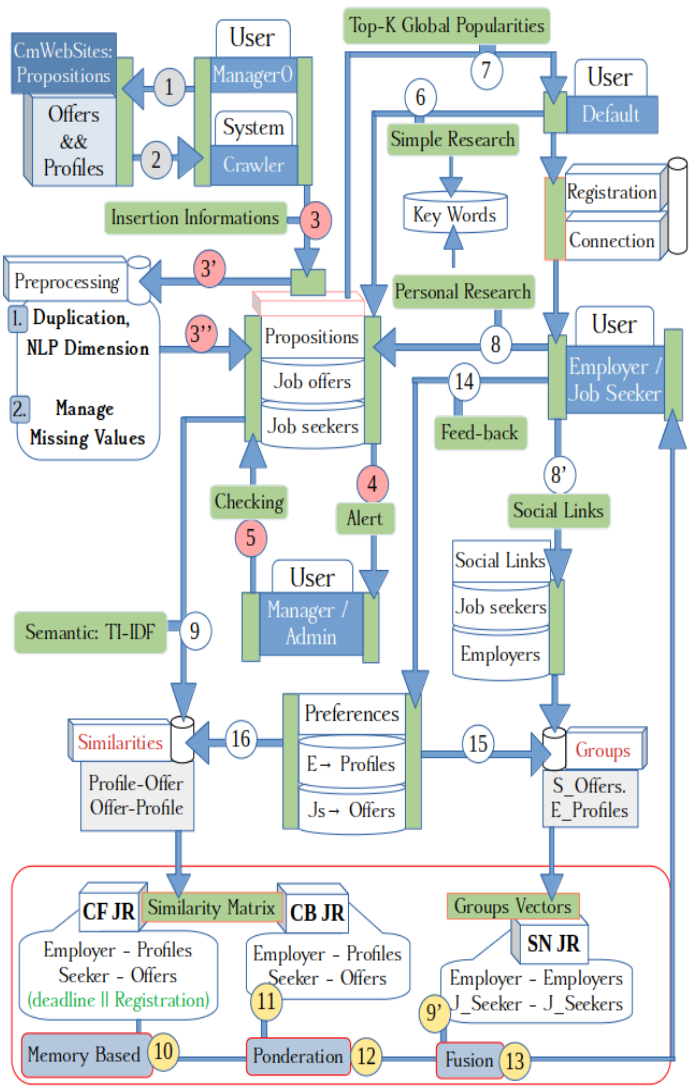


Figure 3. Our Social Job Recommender System Architecturel.

We want to quantify the credibility of a profile in order to use it in search results rankings.

3.2.1. The simple search module.

Each proposal case is composed of a fixed set of features. Initially, these are displayed to the user in descending order of popularity regardless of the activity.

Knowing that the conditional probability is biased by popularity, we use the *Pointwise Mutual Information* (PMI). Indeed, popular proposals will have a higher chance of being recommended than those that have received fewer interactions. The PMI normalizes the correlation score and provides a chance for less popular propositions to appear at the top of the list of related propositions if they are strongly related to the pi proposition in question [35].

Nextly, The query is temporarily stored after being duplicated, cleaned of empty words and rewritten by the corresponding root words. The query containing the most keywords will be used as a reference for searching the others.

The key to the success of this approach is the ability to accurately estimate the similarity between the individual features of a proposal and the query [18].

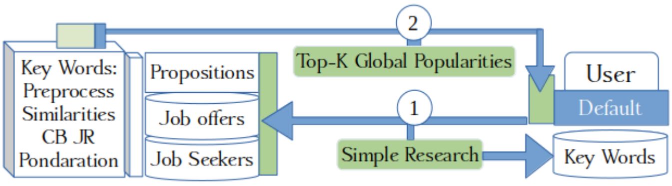


Figure 4. Disturbance from an unconnected user request.

3.2.2. The personalized search module.

It completes the simple search by adding filtering dimensions (user similarities, proposal similarities, feedback or previous searches and social links).

We generalize the notion of preference for user u_i to one proposition p_j on a set of choices (Pu_i) greater than or equal to two by considering it as dynamic following a previous research.

$$Pref_{ex}(u_i, p_j) = 1 - \frac{Rank(p_j, Pu_i)}{\|Pu_i\|}. \tag{7}$$

With $Rank(p_j, Pu_i)$, the position of the proposition p_j in the set Pu_i of those displayed to the user u_i.

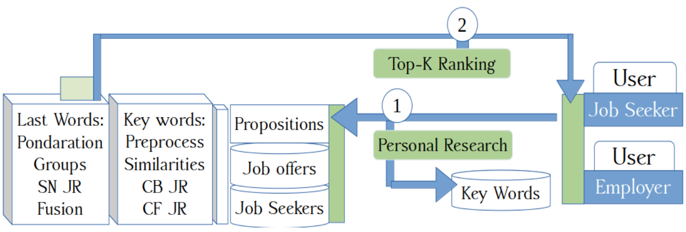


Figure 5. Disturbance from a connected user request.

3.2.3. The feedback module.

Concerning the return on a proposal, it is done at each choice of an element in a list then, by measuring the appreciation by adjusting the predicted rate to the effective rate (the preference matrix is here a ranking in decreasing order of appreciation of each user on all the proposals).

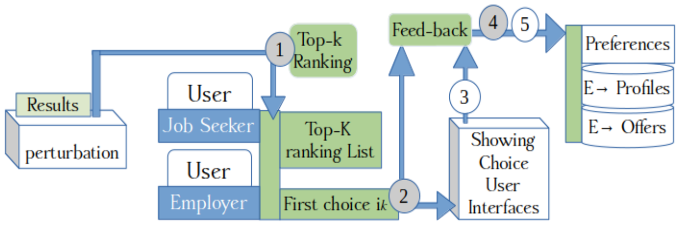


Figure 6. Update user preferences by feedback.

In the path 1, 2, 4, the choice of the t^{th} proposal (marked as seen) among **k** recommended, induces the update of all the **k-1** unrated proposals closest to it by the information first displayed. This function updates the user scores as follows:

$$\begin{aligned} \cup p_{feedback}(u_i, P_k) = \{ & p_j \in NotSeen_{first(k-1)} \\ & (Sim_{Displayed}(P_k, p_j), u_i); \\ & i, j \in \{1..m\}\} \end{aligned} \tag{8}$$

$\forall p_j$ of $\cup p_{feedback}(u_i, P_k)$,

$$Rate(u_i, P_k) += \frac{t \times q}{Q \times (k-1)} \tag{9}$$

with q the number of useful (non-zero) features displayed of P_k and Q its number of useful non-zero features.

In path 1, 2, 3, 5, the previous rate of p_j (empty or predicted) is replaced by the currently taken rate ($Rate_{prev}(u_i, p_j) = Rate_{act}(u_i, p_j)$).

$$Pref(u_i, p_j) = Rate_{prev}(u_i, p_j) - Rate_{now}(u_i, p_j) \tag{10}$$

3.2.4. The 'social links' module.

An estimate of the social affinity rate is given by the average of the rates considered between two users sharing a third in common for the creation of social links.

a) Similarity by manhatan distance

Metric states between two propositions p_1 and p_2, of respective coordinates $a_1[i]_{i\in\{1..m\}}$ and $a_2[i]_{i\in\{1..m\}}$, it is written

$$d_{manh}(p_1, p_2) = \sum_{i=1}^{m}(|a_1[i] - a_2[i]|) \quad (11)$$

Its effectiveness in our context is found in the user relations which are not always direct. Indeed, it is not true that everyone knows each other (direct link), it is thus judicious that the estimation of the probability of a link between two people passes by that of an intermediary (from where the concept of social affinity rate).

$$Rate_{link_1}(u_1, u_2, u_3) = \frac{\sum_{i=1}^{m}(|u_1[i] - u_2[i]|)}{\sum_{i=1}^{m}(|u_1[i] - u_3[i]|)} \quad (12)$$

Assuming that there is a 1 in 3 chance that a user knows two others simultaneously, we take the social similarity threshold between u_1 and u_3 to be 2/3 (Table 5).

Table 5. Description of the modeled user roles

N	$Rate_{link_1}$	Decision
1	[0, 1/3[	none
2	[1/3, 2/3]	Recommendation and consideration in calculations (3.1.3)
3	]2/3, 1[	Recommended and taken into account in the calculations + Considered as effective link without confirmed link until it is.

b) Similarity by Jaccard distance

Rate on the Jaccard distance (d_J) between two users u_1 and u_2 on their respective keyword search histories ($u_1.kw$ and $u_2.kw$) is given by:

$$Rate_{link_2}(u_1, u_2, u_3) = \frac{|u_1.kw \cap u_2.kw|}{|u_3.kw \cup u_2.kw|} \quad (13)$$

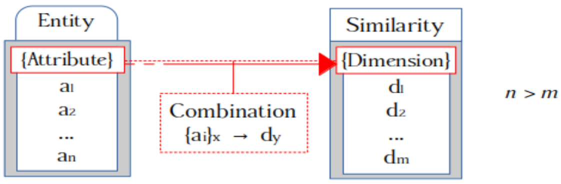
3.3. IMPLEMENTATION

A similarity function will apply between two equivalent dimensions. That is, which have two-to-two attributes of the same type and meaning ([36]).

3.3.1. Grouping of attributes into dimensions.

A dimension will consist of at least one attribute, which can belong to more than one dimension (Figure 7).

Figure 7. Constitution of dimensions for similarity operations.



Finally, we recall that a dimension is a group of attributes that refer to semantically comparable information from the proposition to the application and vice versa (Grouping retained in the Table 7).

3.3.2. Recommendation modules.

Table 6 presents our proposal for a clustering of the dimensions identified as inputs to the similarity functions constructed above.

Whatever $q \in \{1..n\}$ and $q' \in \{1..m\}$; X and Y $\in \{Js, E, O, P, R_{Js}, R_E\}$, $(Sim(Js_q, X), Sim(p_q, Y)) \equiv (Sim(e_{q'}, Y), Sim(o_{q'}, X))$ except for the cases Sim_1 ($\neq \_Sim_1$) and Sim_{Social} ($\neq \_Sim_{Social}$) for whose dimensions change.

a) CB JR: Content Based Filtering module

The guiding idea in this module is that users prioritize the existence of certain characteristics that are specific to them when searching for proposals (Sim_2 (p_q, P), Sim_2 (o_q, O), Sim_3 (Js_q, E), Sim_3 (e_q, Js), Sim_4 (p_q, O) and Sim_4 (o_q, P)) and whose absence as keywords (Sim_5 ($Js_q.K_W$, O) and Sim_5 (e_q.KW, P)) would render them indifferent or even uninteresting to them.

b) CF JR: Collaborative Filtering module

Table 6. Our clustering of dimensions as inputs to the similarity functions.

N	Similarity: Metrics	Module	Dimensions
1	$Sim_1(Js_q, Js)$: d_{TF-IDF}, d_J	CF JR	1, 3, 4, 6
2	$\_Sim_1(e_q, E)$: d_{TF-IDF}, d_J	CF JR	1, 2, 3, 4, 9
3	$Sim_2(Js_q, E) \equiv Sim_2(e_q, Js)$: d_{TF-IDF}	CB JR	1, 2, 3, 9
4	$Sim_2(p_q, P) \equiv Sim_2(o_q, O)$: $d_{T(\alpha=(d_1+d_2)\%, \beta=d_6\%)}$	CB JR	4, 5, 6, 8, 10
5	$Sim_4(p_q, O) \equiv Sim_4(o_q, P)$: d_E, d_J, d_{N-AM}, d_P	CB JR	3, 4, 8, 10
6	$Sim_5(Js_q.kw, O) \equiv Sim_5(e_q.kw, P)$: d_{TF-IDF}, d_{S-D}	CB JR	3, 9, 10
7	$Sim_{Social}(Js_q, Js, R_{Js})$: d_M, d_{S-D}	SN JR	1, 2, 3, 6, 10
8	$\_Sim_{Social}(e_q, E, R_E)$: d_M, d_{S-D}	SN JR	1, 2, 3, 4

The main thought here is that, similar users ($Sim_1(Js_q, X)$ and ($\_Sim_1(e_{q'}, Y)$) will similarly evaluate the proposals made to them and that similar proposals ($Sim_2(p_q, P)$ and $Sim_2(o_q, O)$) will receive similar evaluations. More precisely, it is a combination of the results of the two memory-based collaborative filtering algorithms (Users and then proposals). One using the rating similarities between users and the other using the rating similarities of proposals.

c) SF JR: Social Filtering module

The philosophy of this module of the architecture is that, the users of similar behavior history ($Sim_5(Js_q.K_W, O)$ and $Sim_5(e_q.K_W, P)$) to that of a user u_k (Nu_k) with whom they are in direct link or not (at least one user is close to two others for a group of three), confirm or not (acceptance of a link invitation: ($Social_{Link}(u_k, \cup u_i) = (Accepted, \%similarity)$).

3.3.3. Proposed hybridization.

Content-based recommendations are certainly effective, but they do not evolve much because of the static aspect of the offers and the lack of dynamism of the profiles due to the rarity of their updates. Indeed, job seekers take a long time to add significant new skills or experiences to their profiles).

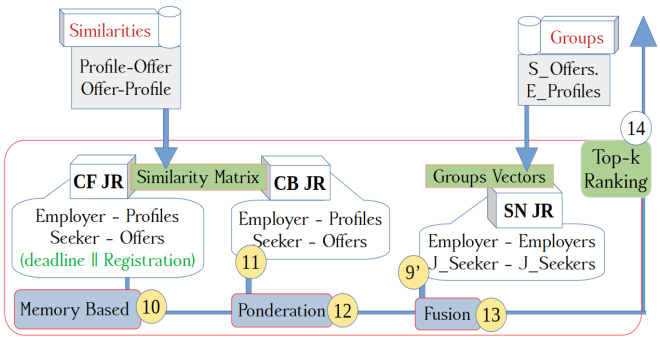


Figure 8. Our Cascade Model recommender.

This gap would be largely filled by collaborative filtering that would be performed in parallel on more dynamic dimensions such as user behaviors in relatively similar preferences.

For any known user, each click is subject to feedback, considering the numerical value of the click for the generation of the following page. Where a search engine would have had displays based on the hardware used, a recommendation engine is deeper because of its advanced filters and its ability to see what would really interest a visitor.

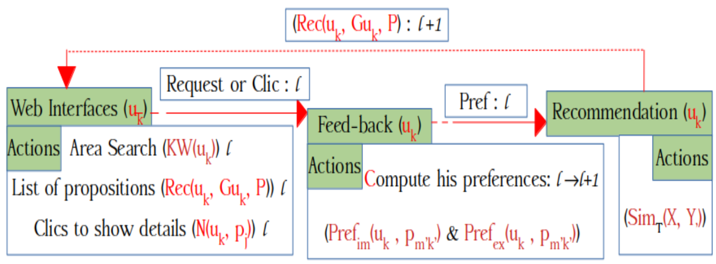


Figure 9. Summary of the interactions between the user and the system to be developed.

We therefore propose that every time a search bar is queried, the proposals that come out of it are perpetually ranked according to the current state of these preferences and those of those around them.

4. Proposed experiments and evaluations

The objective of the system being lists perceived as relevant for a given user, the context presented includes the constraints of profile similarities, candidacy, behavior on the assumptions of popularity and assumed initial ratings, and the appreciations of those who are socially close to him. We propose, therefore, to show that the system will insist on recommending the proposal that best fits the users' expectations (if available) according to the acquired information.

4.1. Minimal experimental environment

In order to avoid task overloads that could result in the incorrect processing of certain data, we propose (Table 8) the minimum hardware configuration:

Table 8. Minimum hardware configuration

N	Computer	Operations
1	M_1: 2 Sessions	Administratives ($Session_1$: Admin; $Session_2$: $manager_0$)
2	M_2: 2 Sessions	Research tests ($Session_1$: Applicants; $Session_2$: Offerors)
3	Online host	Putting into production for the collection of other behaviors

Still, machines 1 and 2 can be a single machine depending on the modules processed.

4.2. Experiments of: the job recommendation

Since it is a data mining system, the functionalities taken into account are the search, the feedback and the recommendation itself on the fields connected to this sector. Note that this is an example and not a restriction because the recommendations can be generalized.

The global methodology assumes the creation of complete initial control profiles and the application of a behavior in equal proportions in each of the experiments but, with different actions to be carried out according to the functionalities that serve as tools for sampling the system responses.

Table 9. Proposed standardization for interpretation

N	Range	meaning	N	Range	meaning
1	[0; 0,1]	Undesired	4	]0,4; 0,6]	Medium
2	]0,1; 0,2]	Indifferent	5	]0,6; 0,8]	Desired
3	]0,2; 0,4]	Strict	6	]0,8; 1]	interview

Follow-up of some blank profiles: (2) *visitors*, (4) *employers* and (8) *job seekers*; where, one makes *Specific Searches* (SS) and the other, *General Searches* (GS); with as respective interests, the quality of the supposed qualifications of the candidates and the supposed work environment given the characteristics of the profile.

4.2.1. Experiment 1: Interest to be determined.

a) Experience Frame

We have chosen to target 20 offers and 20 applications (minimum in keyword filtering). This experiment is centered around the visitor who has no prior information.

Table 10. Proposed reading of the results related to the inclusion of behavioral factors.

Visit	User	Appreciations & Expected system behaviors:
1	supplier	SS:]0.1; 0.6]; GS:]0.2; 0.4] C_1: the candidate search interface
2	supplier	SS:]0,6; 0,8]; GS:]0,4; 0,8] C_2: C_1 + Find the first candidates
3	Seeker	SS:]0,1; 0,6]; GS:]0,2; 0,4] C_3: the offer search interface
4	Seeker	SS:]0,6; 0,8]; GS:]0,4; 0,8] C_4: C_3 + Find the first offers

Collection of recommendations

For a given user u_i and for each new query submitted, depending on whether it is SS or GS and whether the

Table 7. Construction of the dimensions (d_y) to be manipulated on the attributes ($[a_i]_x$).

d_y	$[a_i]_{x=job\_seeker}$	d_y	$[a_i]_{x=Employer}$	d_y	$[a_i]_{x=Commons}$
1	birth_date	1	staff_count	2	location, country
1	birth_place, gender	4	status	9	professional_goal, other_info
3	occup=profession	3	occup=activity	3	domain, $links = \{(u_2, q_{sim}, state)\}$
*	$*Profile =_{id_{prop}\|id_{skr}}*$	*	$*Offer =_{id_{prop}\|id_{emp}}*$	*	*—-$Proposition =_{Profile\|Offer}$—*
				2	tracability=(UserIn, UserCheck)
8	category=type_profile	8	category=type_offer	10	Background = {(id, id_{user}, title, sub_title, reference, state)}
6	matrimonial_state	7	salary, use_time	6	availibility=(begin, end)
		2	job_place	3	title, $KW = \{(id_{kw}, id_{user}, value)\}$
		7	contrat	4	state
		1	$(gender\&old)_{require}$	5	ttal_views, ttal_posit_rate
6	Edu={(id, id_{prop}, speciality, school, begin, end, state)}	10	Mission={(id_{of}, id_{miss}, description, state)}	5	UserRate={(id_{user}, id_{prop}, explicite, read_prop, repeat_prop)}
				10	Knowledge={(id_{prop}, id_{know}, ability, description, state)}

number of proposals displayed is a $top - K$, a $LIST$ data structure is updated as follows:

$$LIST_{Rec}(u_i, (\{Rec(u_i, U, P)_w\})_{w \in \{1..l\}}, req_l, K) = \{(p_j, Index_{Rec}(u_i, Pu_i, req_l), Rate(u_i, p_j))\}. \quad (14)$$

which simply means that for any u_i, the set of recommendations ($\{Rec(u_i, U, P)\}$) according to the number l(an integer) of the query and the number K of elements to display is stored.

Once this collection is done (repeated for each type of research, for each user according to his type), we propose to precede the evaluation of the system for this experiment.

b) Evaluation: using NDCG and ILS metrics

This is not about categorizing users by interest, but about whether the amount of personal information received discriminates against those who do not have an account in terms of search functionality.

With the NDCG mesure

Here, we examine independently (according to the two types of search), the set of recommended lists user by user. The average of this measure for all the users represented in the study gives information on the capacity of the system to offer relevant results even if the ideal proposals are not present (because absent or inconsistent requests) and this, for all the requests of each of them. It is thus a question of an evaluation of the capacity to satisfy the user requests according to the propositions present on the atomic level and in a globally distinct way. The planned calculations are the following:

$$NDCG_K(Rec(u_i, G_{u_i}, P)) = \frac{DCG_K(Rec(u_i, G_{u_i}, P))}{IDCG_K(Rec(u_{u_i}, G_{u_i}, P))}. \quad (15)$$

$$Satisfaction_K(u_i) = \frac{1}{l\_u_i} \sum_{w=1}^{l\_u_i} NDCG_K(Rec(u_i, G_{u_i}, P)) \quad (16)$$

$$Global\_Satisfaction_K(U) = \frac{1}{|U|} \sum_{i=1}^{|U|} Satisfaction_K(u_i) \quad (17)$$

With the ILS mesure

Here, independently of the user type, we want to know how similar the K elements of each list are to each other. We therefore propose to compute for each list, the average of all the two-to-two differences and to make a global average. In view of the context of this work, we find it necessary to know how much the members of the same circle like what is proposed to them. We calculate ILS_K by group:

$$ILS_K(Rec(u_i, G_{u_i}, P)) = \frac{1}{2} \sum_{p_j \in R} \cdot \sum_{p_{j'} \in R'} Sim(p_j, p_{j'}); \quad j \neq j'; R = Rec(u_i, G_{u_i}, P); R' = Rec(u_i, G'_{u_i}, P). \quad (18)$$

And then to find out how similar the propositions of the experience are to each other for the selected users.

$$Global\_ILS_K = \frac{1}{l.|U|} \cdot \sum_{w=1}^{l} \cdot \sum_{i=1}^{|U|} ILS_K(R); \quad R = Rec(u_i, G_{u_i}, P). \quad (19)$$

4.2.2. Experiment 2: known interest.

a) Experience Frame

We have chosen to target 8 supplier accounts for which the 5 best respective and distinct appreciations are associated (40 applications). Knowing that the recommendations take symmetrical paths according to the user type (third chapter: by a q profile or the k^{th} profile), this approach is repeated for the 8 applications with the best similarities with the designated supplier accounts. The objective is to bring out the reciprocity.

Table 12. Listing of possible cases for verification of the inclusion of the social factor.

E - Assumptions	**Behaviors & appreciations**	**Rec(E, A., B.):**
1 - Group(2,3,4)	SS:]0,1; 0,6]; GS:]0,2; 0,4]	Best of 5
2 - Group(3,4,5)	SS:]0,6; 0,8]; GS:]0,4; 0,8]	Best of 1, 5 and 8
3 - New profile	SS:]0,1; 0,6]; GS:]0,2; 0,4]	Best of 3, 4, 5
4 - Old profile	SS:]0,6; 0,8]; GS:]0,4; 0,8]	Best of 3, 5 and 6
5 - Group(3,4,6)	GS:]0,1; 0,6]; GS:]0,2; 0,4]	Best of 6
6 - Group(3,4,5)	GS:]0,6; 0,8]; GS:]0,4; 0,8]	Best of 2, 4
7 - New profile	GS:]0,1; 0,6]; GS:]0,2; 0,4]	Popular ones
8 - Old profile	GS:]0,6; 0,8]; GS:]0,4; 0,8]	Best of 1, 2, 4, 5, 6

Here, we construct the social relations (two-to-two) so that they are registered as 'desired'.

b) Collection of recommendations (lists from simulated feedback)

The collection on the behaviors, for each user according to its type, its group and according to its seniority (Boolean value given by a numerical clustering on the difference between the running time and the recording time, multiplied by the number of requests made).

Table 13. Collection of recommendations with the highest scores (*suppliers|employer: e*)

e \ K	**1 * 2 * ... * index * ... * K**
1	$p_{j_1}1 * p_{j_1}2 * \dots * p_{j_1 index} * \dots * p_{j_1}K$
2	$p_{j_2}1 * p_{j_2}2 * \dots * p_{j_2 index} * \dots * p_{j_2}K$
.	...
r	$p_{j_r}1 * p_{j_r}2 * \dots * p_{j_r index} * \dots * p_{j_r}K$
.	...
l_u_i	$p_{j_{(l)1}} * p_{j_{(l)2}} * \dots * p_{j_{(l)index}} * \dots * p_{j_{(l)K}}$

Table 14. Collection of recommendations with the highest scores (*Job seeker : js*)

js \ K	**1 * 2 * ... * index * ... * K**
1	$o_{j'_1}1 * o_{j'_1}2 * \dots * o_{j'_1 index} * \dots * o_{j'_1}K$
2	$o_{j'_2}1 * o_{j'_2}2 * \dots * o_{j'_2 index} * \dots * o_{j'_2}K$
.	...
r	$p_{j'_r}1 * p_{j'_r}2 * \dots * p_{j'_r index} * \dots * p_{j'_r}K$
.	...
l_u_i	$p_{j'_{(l)1}} * p_{j'_{(l)2}} * \dots * p_{j'_{(l)index}} * \dots * p_{j'_{(l)K}}$

c) Evaluation: using MRR and ILS metrics

We study the ability of the system to reconcile the parties as recommendations are made.

MRR: Here, we jointly examine the values of each proposal recommendation in a bidirectional way. Indeed, by this study (in the manner of a stable marriage problem), the objective is to know to what extent users of constituted social circles prefer each other on the proposals that are made to them. Thus, for each proposal and each user, we will retain its difference in values for each other estimated by the recommendation engine.

$$MRR_K(Rec(u_i, Gu_i, P)) = \frac{1}{|R|}\sum_{p_j \in R}\frac{1}{index_{p_j}}; \quad (20)$$

With: $R = Rec(u_i, Gu_i, P)$.

$$Global\_MRR_K(U, P) = \frac{1}{|U|}\sum_{u_i \in U} \cdot \sum_{p_j \in R} MRR_K(R); \quad (21)$$

With: $R = Rec(u_k, U, P)$.

ILS: This time, depending on the type of user, we will rather try to have an estimate of the average of the reciprocal appreciations. We therefore propose to calculate for each user the difference between the value of his best appreciation and the one he has or would have from the user for whom he gave it.

Taking into account the fact that $Note(u_i.type_1, p_j) \neq Note(u_i.type_2, o_j)$, the formula is rewritten:

$$\begin{aligned} ILS_K(Rec(u_i, G_{u_i}, P)) = &\frac{1}{2}\sum_{p_j \in R} \cdot \sum_{p_{j'} \in R'} Sim(p_j, p_{j'}) \\ &+\frac{1}{2}\sum_{o_j \in R_o} \cdot \sum_{o_{j'} \in R_o} Sim(o_j, o_{j'})'. \end{aligned} \quad (22)$$

$$\begin{aligned} R = Rec(u_i, G_{u_i}, P); R' = Rec(u_i, G'_{u_i}, P); \\ R_o = Rec(u_i, G_{u_i}, O). \end{aligned} \quad (23)$$

$j \neq j', (p_j, p_{j'}) \in Pu_i.type_1$ and $(o_j, o_{j'}) \in Ou_i.type_2$ with $Pu_i \cup Ou_i = P$ the set of propositions.

5. Results and discussion

5.1. Results

The search proposal for the number of recommendations is displayed between two updates by varying K between 5 and 10 (interval taken in the literature) for all the proposals which respectively included ([1, 5], [1, 6], [1, 7], [1, 8], [1, 9] and [1, 10]), then by recovering each time the return values of the various metrics.

5.1.1. Overall analysis and assessment.

According to the values taken by K, we compare the $NDCG_K$ to the MRR_K according to K then, we directly compare the ILS for the cases where $NDCG_K$ and MRR_K are both maximal.

If the ILS are close in a normalized way then, the system recommends as well to users on whom information is recorded as to those on whom the only information comes from their growing activities. If they are too far apart, then the challenge wille be to make sure that no matter what the cases are, for those on whom the information is known, the system recommends better

5.1.2. Contributions of the current work in JRSs.

They are diverse contributions according to the prisms of observation in the literature. We count, a recall of the fundamentals, a proposal of current assessment in the field, a proposal of an agile approach of conception for similar works and an essay in the procedure of its incorporation in an existing system.

An original method considering those used in the literature: We have proposed a test protocol for a perceived recommendation system to answer the need to always end up recommending the most significant proposals to the users who are processing search. In order to quantify these experiments, we have proposed and then readapted the evaluation concepts to make them most suitable (*in our opinion*).

A review that can serve as a basis for other similar investigations: The first chapter is a literature review type contribution because of the grouping it offers on the main architectures available from the fundamentals to the present day. This contribution can be used for another implementation proposal that would no longer be preliminary like ours.

An in-depth search for relevant variables: Indeed, most of the consulted datasets (even similar by the addressed problem posed concerns of non-exhaustiveness), do not offer many comparison options according to the highlighted properties (even in case of filtering based on knowledge).

5.2. Discussion

The following discussion outlines the implications of our work in JRS and presents their limitations.

5.2.1. Between estimation and redefinition of treatments.

Confidence estimation of effective matches: Given the set of variables available from the first search, expectations of the proposed ILS based on interests (provider or researcher in an area). Our hypothesis is that the more diversified the information about the user, the more his chances of satisfaction thanks to a fine filter are reduced. However, the degree of trust of recruiter-job seeker associations is invariably achieved for mutually found proposals (the possibility of confirming recommendations) by the links of those who are socially close to them.

The redefinition of the treatment of dimensionality: An important remark on the non-use of the SVD model in view of the sizes of the manipulated matrices is that, its application remains effective for items varying very little in availability and in number and thus, it would have been useful only for recent proposals. Indeed, the durability of job-related proposals is not as long as those of items usually found on e-commerce sites, due to the deadlines included in the offers and the varied and unevenly distributed availabilities in the applications. Moreover, SVD is specific to dimensionality reduction work, and the attribute groupings made during the design of the architecture constitute our approach in this sense.

5.2.2. Between design and implementation: limitations.

Traceability is not incorruptible: As currently conceived, traceability needs to be strengthened along with security in order to create confidence in the proposals that the system would offer. Indeed, it does not prevent users from being influenced by those who make too general searches or by those in the circle who do not make any.

From serendipity to effective relevance: They are therefore testers like laboratory assistants who do not stray from the test protocol even if the results are not known in advance. In fact, the results are interpreted according to the respective pre-established roles that do not logically oppose the fact that a proposal from a domain or sector not related to that of the user is of interest.

6. Conclusion

Our approach around a system of recommendation for profiles based on professional social networks goes from the establishment of the bases allowing to better define the problem in its generality, while passing by a proposal of preliminary implementation around the identified key concepts.

Although the results are strongly dependent on the completeness of the records, the reduction to one domain allows the generalization of the outputs for a presentation of the logic around work because, the implications retained are interactional in nature and related to data mining ([9]) for a contribution to the resolution of a deep socio-economic problem ([37]) that is unemployment.

Our current contribution is intended to be the precursor of work for an implementation that will have its place as a true professional social network. A comparable work (although not including social links) would be that of [22]; only, we detail the multidimensional treatments of the data offering therefore, more option by taking up the investigations made by [21].

7. Future work on the current system

In addition to being an introductory work to a more elaborate implementation in a practical way, the expectations are articulated first around a research on the hypothesis that an increasing number of applicants having been recommended for a given offer would reduce its availability time; then around the resolution of difficulties such as to answer the question of the evaluation of the chosen statistical methods used to group the variables for improving the constitution of the current dimensions; to answer the integration of the management of the calculation times of the recommendations in view of the lack of a proposal of calculation of the complexity of the path of the recommendations on the capacities of the system from a point of view of scaling.

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