A Static and Dynamic Recommendations System for Best Practice Networks

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Abstract. Semantics computing technologies may be used to provide recommendations and stimulate user engagement in many kinds of services, such as social media, match making, best practice networks, technology transfer, etc. The recommendation metrics used take into account both static information and dynamical behaviors of users on a Social Network Platform. The recommendations provided include those realized taking into account also strategic and random users. The set of recommendations have been assessed with respect to the user's acceptance, which allowed to validate the solution and to tune the parameters. The experience performed in creating and validating recommendation systems adopted for ECLAP and APRETOscana best practice networks is described and results obtained are reported. The identified model has significantly increased the acceptance rate for the recommendation on ECLAP.

Keywords: best practice network, semantic computing, recommendations, social media, grid computing, validation model.

1 Introduction

Semantics computing technologies may be used to stimulate user engagement in many kinds of services, such as social media, match making, best practice networks, technology transfer, etc. The semantic computing is typically confined on the server side to provide recommendations. Despite to the massive success of social media, most solutions have limited semantic computing capabilities and provide simple recommendations about possible friends and on marginally similar content items. Among the possible combinations of suggestions related to users, content, ads, and groups only some of them are viable [1]. Recommendations should be computed on the basis of relationships U→U, G→C, C→U, etc. where U means User, G: Group and C: Content/Item, thus C→U means proposing Content suggestions to Users. The earliest solutions for guessing users' intentions have been based on keyword-based queries (i.e., sponsored search, or paid listing), which places ads and/or recommendations in the search results; and content match, also called content-targeted advertising or con-

adfa, p. 1, 2011.

textual advertising, which places ads on the basis of the web page content and content similarity [2], [3]. Contextual recommendations are widespread and many systems can extract keywords from web pages to produce suggestions [4], sometimes using semantic approaches [5]. In order to predict which terms describing a product or service are more relevant, models based on clustering, collaborative filtering, logistic regression, etc., are used [6]. User's ranking and reputation are connected to recommendations and trust and are becoming essential elements of web-based collaborative systems [7]. Implicit trust networks have been employed to incorporate trust and reputation [8], obtaining trust relations from a record of results in previous recommendations, by semantic reasoning and inference mechanisms upon recorded data.

In this paper, we reported the experience performed in creating and validating recommendation systems for services including complex descriptors: (i) ECLAP http://www.eclap.eu a best practice network and service derived from research tools and solution for providing services towards the community of performing art institutions; ECLAP includes about 120000 contents, 1900 users and 35 groups; (ii) APRETOscana http://www.apretoscana.org a best practice service for supporting industries and research institution to match demand and offer and accessing to European commission founding; about 1800 users, 15 groups. They need recommendation systems for C→U, U→U, G→U, C→C in order to facilitate contacts. Contacts are consolidated by establishing stable connections among colleagues. Initially, both the above solutions where set up with a recommendation system developed for a medical best practice network, namely, Mobile Medicine [1]. The results obtained were not satisfactory since the context of ECLAP and APRETOscana were quite different and thus a study phase has been started to reshape a more focused and tuned recommendation system.

To this end, a new model to compute similarities and propose suggestions has been developed. The proposed model to present suggestions has been validated. The validation aimed to verify if the modality and the parameters used to propose the recommendations where acceptable for the users in the domain. This model considers both the user profile and the information extracted by analyzing the actions that users perform on contents in the recent time. The list of recommended friends/colleagues it is not comprised only by the users they can more probably accept but is realized taking into account also strategic and random users, basing on the serendipity philosophy.

2 Requirements Overview

In this section, the main requirements for the recommendation system that can be adopted in best practice networks are discussed. The requirements have taken into account the lesson learnt from the management of a number of thematically different best practice networks, such as: ECLAP on performing arts, APRETOscana research and technology transfer, Mobile Medicine medicine and emergency situations, IUF of CSAVRI (http://iuf.csavri.org) e-learning and new companies, etc.

The following requirements are referred to user to user (U→U) recommendation systems that have to provide reasonable suggestions to users basing on:

- both static and dynamic aspects of user behaviour, and of the content descriptors. User profile static aspects may include: age, languages, sex, city, job, education, preferred content, joined groups, etc;
- both new and regular users, avoiding the problem of the Cold Start. The new users often risk to do not have any recommendation since their static data are frequently not compiled and dynamic data are not yet collected;
- the last performed dynamic actions of the users and progressively forgetting the older (less recent) activities;
- the experience of the users that may have similar interests, intentions and/or temporal evolution in the portal;
- stimulating the connection to users in successive activities on the portal by creating side effects in their home pages (e.g., content posted, new connections, new groups). This action allows increasing the mean number of connection per user, and helps peripheral users to get connected with those with greater centrality, higher number of connections, etc.
- the complementary suggestions that could be unexpected for the recipient, but that can be accepted if well motivated (e.g., he likes this music genre, he visited Paris recently, etc.). So that, the system could learn from the acceptance of those new connections about the user preferences, despite the lack of related content and of similar colleagues;
- progressively estimate of the recommendations and not constraining the system to perform the systematic recomputation of all of them at each change of the dynamic aspects of the user profile and behaviour;
- an identification and use of the minimum number of parameters as a compromise from computation and effectiveness. This means that: (i) the computational complexity (the costs) of recommender system may be strongly influenced by the number of parameters taken into account; SVD/PCA and other statistical techniques can be used to reduce them as much as possible; (ii) the acceptance rate of a recommendation system may strongly depend on the presentation of the recommendations to the users.

3 Recommendations Model

As previously mentioned, recommendations can be computed through several different techniques. In most cases, the elementary operation is the similarity distance among descriptors. The estimation of distances among elements can be computationally expensive in the presence of complex descriptors and/or millions of items, depending on the complexity and on the high number of the descriptors. In the following, the model adopted in ECLAP is presented.

The **user static profile** consists of the data that change slowly over time [1]. In generalist social networks, the static profile is usually not very detailed: users do not like fill form online at the time of registration and sometimes tend to provide false information. In small thematic networks, however, this kind of information is much more reliable. The static profile takes into account: general information (name, surname, gender, date of birth, personal description, place of origin, spoken and mother languages), contact information (email and instant messaging contacts), school and work (school level, name of school or university, type of employment, name of the place of work) and interest (a list of categories of interest). Some data are coded by using specific standard like: ISO 3166-1 alpha 2 and ISO 3166-2 for place of origin, ISO 639-1 for spoken languages. Type of employment and categories of interest depend on the portal usage domain. Moreover, the static profile considers also subscribed groups, friends list and user's interested taxonomy topics.

User last N Interactions on	**Corresponding collection of multilingual Taxonomy descriptor documents**
Promoted	Arti figurative Danza Balletto, Arti figurative Danza Balletto Russi, Performing Arts Russian Ballet, Lettres Danser Ballet Russe…
Downloaded	Performing Arts Modern Dance Performance Utopy, Un altre Recerca Gènere Tema, Performing Arts Modern Dance Performance Utopy, Andre Forskning Genre Om, Andere Forschung Genre Gegenstand…
Played	Video Musicale Rock, Video Musical Rock, Video Music Rock, Video Musique Rock…
Favorites	Drama Gènere, Coreografia Rendiment Contemporani Dansa Arts Escèniques període històric Arts Escèniques, Performing Arts Modern Dance Performance Utopy, Drama Genre….

Table 1~~1~~. Example of dynamic profile taxonomy based

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The **dynamic profile** is established on the basis of the actions the users perform on the portal. In ECLAP, the dynamic profile considers four types of user interaction: content seen by the user (played), user's favorite content (favorites), promoted and downloaded content. The user profile is built by providing a hierarchical taxonomical classification for each of the these categories considering the N last recently used content for each of them. Table 1 shows an example of a user that in the last period has watched several videos of rock music and promoted Russian ballets.

3.1 Users proximity evaluation

On the basis of the above mentioned aspects, the calculation of the proximity (*prox*) between two users A and B is defined by a linear combination of the values of proximity calculated for the static ($prox_s$) and dynamic ($prox_d$) profile aspects and defined as follows:

$$prox(A,B) = prox_d(A,B) \times \gamma_d + prox_s(A,B) \times \gamma_s \qquad (1)$$

Where: γ_s , γ_d respectively weight the relevance of the static and dynamic distance.

$prox_s$ is defined by the eq. (2) as a function of static similarity between users relative to: spoken languages (v_{lang}), locality (v_{loc}), interests (v_{int}), common friends (v_f), subscribed groups (v_g), age (v_{age}), interested taxonomy topics (v_{tax}) as proposed in [1].

$$prox_s(A,B) = F\left(v_{lang}(A,B), v_{loc}(A,B), v_{int}(A,B), v_f(A,B), v_g(A,B), v_{age}(A,B), v_{tax}(A,B)\right) \quad (2)$$

$prox_d$The dynamic proximity is calculated using the value of similarity (*score*) provided by the system of indexing in Lucene and given by the Lucene's Pratical Scoring Formula in the multilingual documents created from document as described in Table 1. The dynamic profile is based on the multilingual document (doc_i) which is indexed. In this way, the dynamic proximity distance is defined as:

$$prox_d(A,B) = \frac{score(doc_A, doc_B)}{\max_{X \in queryResult} score(doc_A, doc_X)} \quad (3)$$

The score provided is normalized using the maximum score given to documents resulting from the query.

3.1 Other Recommendation Criteria

The static and dynamic aspects satisfy a part of the requirements but not all. They are unsuitable to provide recommendations: (i) in the case of cold start (new users), (ii) that may stimulate new and unconnected users to get in contact to strong reputation colleagues, (iii) to strong users about new users that may need help in entering into the community. To this end, additional recommendation types have been added:

- **Strategic recommendations** are those that recommend to users who have a few colleagues those with highest number of connections and vice versa solving point (ii) and (iii).
- **Random recommendations** consist in suggesting to users a random selection of other users (perhaps with completely different to their own interests), driven by curiosity to new content, can create contacts with new friends, expanding the list of his interests and thus changing his dynamic profile.

As described in the following, the early validation presented in this document aimed at assessing the acceptance level of the ECLAP users about the proposed recommendations: static, dynamic, strategic, and random. The questions was: provided that the recommendations are performed by presenting some rationales about the similarity, which of the above mentioned aspects and recommendations would get the highest relevance from the user point of view, thus stimulating them to get in connection.

4 Computational Architecture

The architecture of recommendation system (Figure 1) consists of: the ECLAP portal, the ECLAP Storage Area and ECLAP Back Office, implemented by using AXMEDIS AXCP tools [9]. The ECLAP portal is responsible for: (i) collecting user static and dynamic information and storing all data respectively in the Static and Dynamic Data repository; (ii) creating users connections and store them in the User Relationship repository; (iii) providing suggestions to users and (iv) providing a survey to get a feedback by users for assessing and tuning the system. Finally, the ECLAP back-office is responsible of evaluation recommendations according to the above presented model and executes on a distributed system multiprocessor algorithms:

- ***Potential Friends***: it calculates the static proximity between users, performing the computations related to the new users, and renovating the computations for the less recently updated. This approach keeps the estimation as much light is possible to update the static aspects that slowly change over time.
- ***S.L.I.M.*** (Suggest Lucene Index Manager): it deals with the dynamic data by building dynamic profiles and indexing them in the Lucene engine. Also this process is periodic and estimates the new version of the documents (Table 1) indexing them incrementally, thus updating only the dynamic profiles of the most active users and those that have significantly changed their dynamic descriptors.
- ***US.TER*** (User Suggester): it calculates the vector of U→U recommendations by using the above mentioned method: (i) eq. (2) as described in the following, by considering value produced by *Potential Friends* and SLIM, (ii) random, and (iii) strategic.

Commento [m1]: non mi è molto chiaro.....

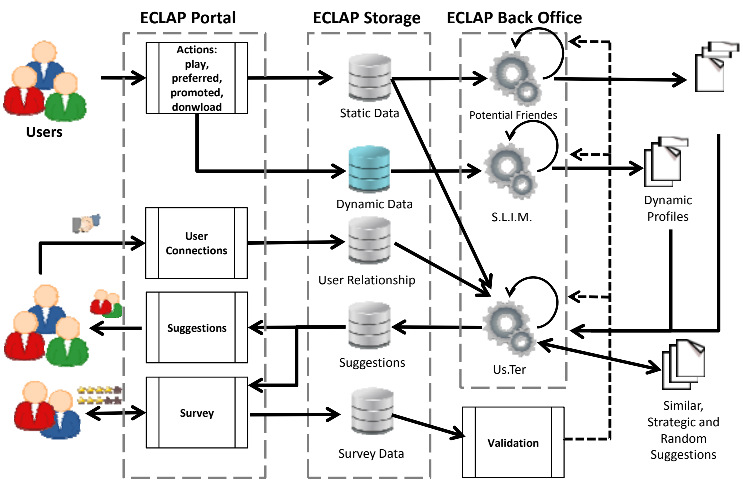

Fig. 1~~1~~. Computational Architecture of the ECLAP Recommendation System.

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Typically, suggestions are provided with the 50% of kind (i), and 25% for kinds (ii) and (iii). The number of recommendations presented to the user have to be typically a small part of the whole recommendations computed, leaving at the users the possibility of taking more recommendations on demand.

The architecture is implemented as grid processes to take advantage from the distributed computing and to calculate/update progressively the needed data for generating recommendations. To have fresh suggestions, grid processes run as periodic processes according specific schedules defined by the administrator.

5 Validation & Results

Before moving to the real analysis of results achieved a system for validating the method. This allows tuning the system to match the user's preferences providing them better suggestions. A survey has been defined and posted on the portal. It proposes to each user the profile of 10 potential friends: each user is called to provide an answer to the question "*Are you interested in getting contact*?" by giving a vote (from 1 to 5) to indicate how much he is interested in the connection. To justify why the system asks to each user for (possible) potential friend, some motivations have been provided in the survey, as shown in Fig. 2~~Fig. 2~~. Such motivations have been built by considering:

a) ***similar users:*** similarities are shown according to the user profile as described;
b) ***strategic users:*** are motivated according to their activity or how much they are connected (or are not connected) to other users, etc.
c) ***random users:*** are randomly selected and motivated providing user profile details such as: the list of groups to which the users are registered, the profession, and the taxonomic classification of the last content viewed.

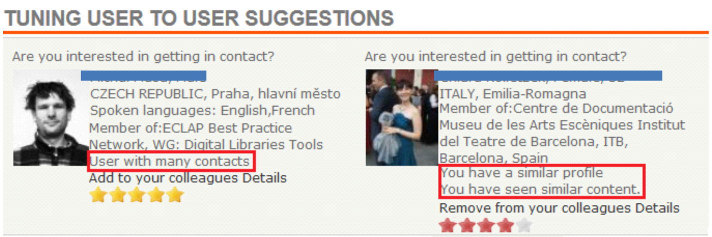

Fig. 2~~2~~. Examples of the online survey (names have been obscured).

This should avoid that a user is faced with a recommendation without any details and thus considering it as not relevant. The range of the votes is 1-5. It is possible to consider the following three categories: *useful* ('Yes I want the user as my colleague!') if the vote is 4 or 5; *not useful* ('No I do not want the user as my colleague!') if the vote is 1 or 2; *not relevant* if the vote is 3 ('I do not know'). In order to estimate the model weights, a number of users have been involved into a learning phase in which we

Commento [m2]: questo forse si può togliere

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Formattato: Tipo di carattere: Grassetto, Non eseguire controllo ortografia o grammatica presented to them set of potential colleagues to be voted. Since the recommendations proposed were of two kinds, (a), (b) and (c) above, the validation votes have been taken into account in different manners, as reported in the following subsections.

Commento [m3]: DOMANDA: tipo uno: similarità valutata considerando aspetti statici e dinimici. tipo due:criteri alternativi per stimolare gli utenti in cui rientrano 'strategic' e 'random' users. Quindi: non dovrebbe essere (a), and (b), (c) ???? tipo1 = (a) e tipo 2 = (b) e (c) ???

5.1 Validation of Static, Dynamic Recommendations

This analysis aimed at estimating a linear model to the vote of users considering the values of metrics. More precisely, the model is defined by the following equation:

$$prox(A,B) = v_{lang}(A,B)\cdot\gamma_{lang} + v_{loc}(A,B)\cdot\gamma_{loc} + v_f(A,B)\cdot\gamma_f + v_g(A,B)\cdot\gamma_g + v_{age}(A,B)\cdot\gamma_{age} + v_{tax}(A,B)\cdot\gamma_{tax} + prox_d(A,B)\cdot\gamma_d \quad (4)$$

Where γ_i coefficient weights the relevance of the distinct proximity factors. The number of votes collected largely exceeded 10 times the number of γ_i weights of eq. (4). This allowed us to perform Multilinear Regression to estimate the weights as reported in Tables 2 and 3. Table 2 indicates that the estimated regression model has been confident: R_{square} represents the percentage variation in vote given by users explained by the model, and it is the square of R_m and it indicates the quality of the predictive model. F is the ratio of the variation of the votes that are explained and those that are not explained by the metrics: it is the variation of residuals. $F_{relevance}$ represents the probability that the vote can be random compared to the values of the metrics. In Table 3, γ_i weights, Stat-t and P-values of each metric are present. Stat-t is the ratio between the single metric coefficient inside the model and its standard deviation.

Table 2~~2~~. Results on the data collected.

Results (MR, first time)	
R_m	0.9624
R_{square}	0.9262
F	131.7795
$F_{relevance}$	2.3389E-33

Table 3~~3~~. Multilinear Regression Coefficients analysis

Metrics	Coefficients (γ_i)	Stat-t	P-value
$prox_d$	-0.0047	-0.7312	0.4673
v_{tax}	0.006	0.3906	0.6974
v_{age}	0.0328	4.7163	1.3753E-05
v_{lang}	0.032	10.2136	5.4563E-15
v_{loc}	0.0408	6.0958	7.2905E-08
v_{groups}	0.024	3.9658	0.0002

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P-value indexes how the votes, compared to each metric, are relevant in the model: the higher is the Stat-t value and lower is the P-value. The analysis of the relevance of each metric used for the generation of suggestions (Table 3), reveals that the relevance of v_{tax} and $prox_d$ are rather low. For this reason, a new Multilinear Regression has been realized and the results are reported in Table 4 and Table 5. The results highlighted that users selected their friends mainly on static aspects and less on the taxonomical modeling of the content. The data shows that the motivations that drive users to tighten social connections are: age, spoken language and location.

Table 4. Results on the data collected . **Table 5.** Multilinear Regression Coefficients analysis.

Results (MR, second time)	
R_m	0.9620
R_{square}	0.9254
F	201.4967
$F_{relevance}$	1.6585E-35

Metrics	Coefficients (γ_i)	Stat-t	P-value
ν_{age}	0.0324	5.0306	4.1064E-06
ν_{lang}	0.0154	11.6651	1.3683E-17
ν_{loc}	0.0131	6.1930	4.4967E-08
ν_{groups}	0.0027	4.4234	3.7840E-05

5.2 Validation of other kinds of Recommendations

On the basis of the votes collected, the strategic suggestions have been considered very interesting and useful by users, that in the 73,81% of time admitted to have been convinced of getting in connection with the proposed users. On the other hand, randomly provided users did not give a real stimulus to get connected. In fact, in this latter case, the percentage of votes in the three categories have been very similar: *useful* 32,58%; *not relevant* 37,08%; *not useful* 30,04%.

5.3 Impact of the produced model on acceptance rate of recommendations

Once discovered these issues, the derived model has been adopted in ECLAP, substituting the previous model that was in place since 28 months. Therefore, from November 2012 up to now, the new model has been adopted, and use data have been collected, in order to assess the users’ appreciation. From the data analysis, it can be noted that the increment of the average number of accepted recommendations is of the 42%: ECLAP registered an averaged increment of 42% of the accepted recommendations per week in the period Nov 2012 - Feb 2013. Moreover, by comparing the same periods: 'Nov 2011-Mar 2012' (old model) against 'Nov 2012-Mar 2013' (new model), an increment of connections of 241% has been registered.

6 Conclusions

In this paper a recommendation system integrated in a collaborative best practice portal has been described. The system provides to users a list of potential colleagues based on both static information and dynamical behaviors of users. These aspects have been used to define metrics that combined together allow to estimate a proximity assessment between two users. The model includes a set of weights to define the relevance of the different metrics. The acceptance rate of the recommendation is not only an aspect related to user proximity but also the manner by which the recommendations are proposed. In this work, we have validated the model to propose different kinds of recommendations: static/dynamic based, random and strategic. The assessment performed allowed us to tune the recommendation system increasing the previous solution. The analysis reveals that the system has been useful to increase the number of acceptance rate of the new connections and suggested the actions to be performed in order to improve the recommendation system efficiency.

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