PRES – PERSONALIZED EVALUATION SYSTEM IN A WEB COMMUNITY

A Conceptual Model Designed to Evaluate Reputation in Order to Achive a Personalised View on the System for Each User

Lenuţa Alboaie

Department of Computer Science, "A.I. Cuza" University of Iaşi – 16, Berthelot, 700483 Iaşi, Romania

Abstract: The purpose of the PRES model is to build a flexible and easy way to manage resources in a personalized manner. Our proposed model assures for every user that his preferences are important and permits the formation of some homogenous groups on the basis of these preferences. The homogeneity is due by the relations resulted from the explicit and implicit evaluations of resources. The purpose of the proposed model is to build a flexible way to filter irrelevant resources for users. In this way, a user which is member to a community based on the PRES model will dynamically see information that he/she is most interested in.

1 PREAMBLE

In this moment the WWW space stores large amounts of data which are continuously growing. The main problem that appears is to find solution to use efficiently the existent resources.

A first step to solve this problem is to associate metadata to resources. As a fact, it is a manual classification process performed by the user (E.g. delicious, digg.com). This direction is a part of explicit Web that is realized through explicit activities as tagging or digging.

An important direction, using the above solution, is to obtain data/information by observing and analyzing the user actions. Thus, we enter the space that is known as implicit Web (O'Reilly, 2005). An important drift of it is collective intelligence domain (T. Segaran, 2007).

In this context, this work proposes the analysis and projection of a prototype of a reputation's personalized evaluation system in a Web community (PRES - P*ersonalized Resource Evaluation System*). The originality of this approach consists in the chosen perspective to accomplish the evaluation.

This work is structured as follows: in section 2 we describe a short survey on the present situation (O'Reilly, 2005, H.Zhuge, 2008). In the next section we present the problem, we explain why such a system is necessary and we present the proposed

model. In the fourth section we analyze the benefits of the proposed system. The article ends with an overview on the discussed domain, mentioning the future directions.

2 ACTUAL SITUATION

At this moment there are many sites that collect various information about thousands or even millions of people on the Web. This information is obtained often without even interrupt user actions with questions. His behavior and profile can be obtained from this information using different techniques like machine learning and statistical methods

In the collective intelligence spectrum we have two different approaches, one exists due the information furnished by users (e.g. Wikipedia). The other part of the spectrum is based on different algorithms which allow obtaining new information that enhance the user experience. An important example in this sense is Google, which uses links to rank web pages, but also collects and process data obtained from situations when advertisements are clicked.

Other examples consist of web communities that use recommendation systems (Massa, B.Bhattacharjee, 2004). In this cases there are

collected information like purchasing history and user characteristics, and the system make proper recommendations based on them (e.g. Amazon, Netflix).

Other examples consist of web systems which use reputation systems (Golbeck, Hendler, 2005). Reputation systems are extremely useful in those communities where the users have to interact with some resources posted by other users or they have to interact with other users. (E.g. YouTube, Slashdot, Flicker). In these situations, using experience of other users would be very useful. Also, reputation systems are useful in setting some evaluation levels for users and resources (e.g. more or less interesting resources). There are a variety of reputation systems. A well-known system, mentioned before, is Google *Page Rank* (A. Langville, C. Meyer, 2006) that is based on complex algorithms that assure the web page ranking.

Another reputation system is that used by *eBay*. The system assures a feedback profile for each member.

Each feedback consists of a positive, negative or neutral value (these values are obtained from the ratings of the transaction partners) and a short comment.

Everything2 is a knowledge base that contains reputations system both for users and their posted articles. The system is based on anonymous votes of other users which determine positive or negative ratings. Negative evaluated articles are deleted. The users are evaluated on the basis of the number of their submitted articles (and not deleted) and on the average of their associated values.

Such a system implies some problems: new users posting articles that receive negative feedbacks may appear. These articles will be deleted, thus discouraging new postings by such users. Even the experienced users hesitate to post new articles which they consider as being not very good, because the received negative feedbacks are not deleted. Also, in this kind of system the re-actualization of older articles is less appreciated.

Slashdot has a reputation system named *karma*. In this system there are moderators that can make the evaluations in a similar way to the system Everything2. Every user may become moderator if he has a good karma obtained on the basis of the ratings associated to their comments. But this moderator state is temporary until he uses the available votes. This evaluation system is criticized because it is weak on issues like Anonymous Coward or sock puppets (R. Falcone, S.Barber, L. Korba, M. Singh, 2002).

Another system we referred here before is Wikipedia that represents an online community containing a great number of users, but not using a formal reputation computation mechanism.

As in the previously discussed systems, a less visible user hierarchy exists. All users, on the basis of their contribution, may receive the so-called *barnstar* acknowledgement. Although one can follow each user posting history, it does not exist a particular rating system.

3 PRES MODEL PROPOSAL

3.1 Context

In section 2 we have discussed a set of reputation systems (R. Falcone, S.Barber, L. Korba, M. Singh, 2002), but in all these related approaches we do not find a personalized evaluation. In this section we explain what a personalized evaluation means, from our point of view.

In a Web community there exist a lot of resources. There are human resources and other types of resources. The people have either different or similar profiles. Therefore, they are interested in either different or similar resources.

We quantize this interest with values which are provided by the user for other users or resources. Also, this interest will have an indirectly computed component. We give a simple example here, the other cases being analyzed in section 3.2. We have the situation when a user evaluates favorably one or more users. These users evaluate favorably a given resource. Even if the user does not evaluate directly that resource we will consider an implicit favorable evaluation (J.Golbeck, J. Hendler, 2006). Thus, the user has the chance to access more relevant resources for him.

In our system there is no it does not exist an absolute value of good or bad resource characteristic. A resource can be good for a set of users but not useful for other set of users.

In section 3.2 we establish a set of metrics (J. L. Mui, 2002), taken into account by the evaluation mechanism, for the purpose of measuring the usefulness of a resource for a given user.

Whenever new users become community members they can interact with the users corresponding to their preferences. Also, they will be able to access much faster the proper resource set. This represents the general direction our system is based on.

3.2 The Proposed Model

First we define the vocabulary used in the developing model. We also specify the used notations and their semantics. The system will contain:

- Users which know other users.
- The list of the users considered to be interesting for a user.
- Users nominated by a community as evaluators. We use notations $E_1...E_n$ to indicate the community evaluators. These evaluators are in fact some reviewers. They will be useful for the new users which have not established their own knowledge list yet.
- Known person list of a user. Initially, it contains the community reviewers list only.
- Resources – their definition is made accordingly to the definition given by (T. Berners-Lee, 1998).

So, in our system one considers as resources everything having an identity (e.g. electronic document, an image, a service and eventually a collection of other resources). There are considered as resources those that cannot be accessed directly via Internet (e.g. human beings, organizations)

- *Worth* – this parameter is a metric. This metric signifies a given rating, according by a user to a resource or a user. Also, the worth can be obtained (quantized) indirectly.

This parameter – *Worth* – takes the following values:

- 1 = useless/spam
- 2 = poor
- 3 = worth attention
- 4 = good
- 5 = exceptional. We note this limit with *MaxWorth*.

We think of using the 1-10 interval for possible values for Worth metric, this approach assuring higher granularity in resource evaluation. We prefer the above specified selection to simplify the model.
In future works we will analyze if this aspect has a major influence on the resource evaluation manner.

We will use a set of constructions which have the following associated semantics. In fact, these constructions can be mathematically considered as functions (eventually partial functions) or, from the implementation point of view, they are considered associative tables:

- Explicit worth of a resource: *WE_UR (user, resource)* – explicit worth, represents the rating for a resource, this rating being given manual by a user
- Implicit worth of a resource: *WI_UR (user, resource)* – implicit worth, represents a rating inferred from the set of existing ratings from the known person list of a user
- Explicit worth of a user: *WE_UU (user, user)* – explicit worth, represents the rating for a user, and the rating is given manual by the user to another user
- Implicit (deducted) worth of a user: *WI_UU (user, user)* – measure how close are his preferences to the others preferences (The preference can be considered: the accepting degree of a point of view or the appreciation degree of a piece of art).

Implicit we consider that we have:

WI_UU (user, evaluator) = MaxWorth;

If an user evaluates an evaluator in an explicit manner, then this evaluation - *WE_UU (user, evaluator)* – will have priority.

- we consider the function *WU(user, user)* for every pair of *(user, user)* from a Web community

Its value will be *WE_UU (user, user)* if there is an explicit evaluation (different from 0), otherwise its value will be *WI_UU (user, user)*. So, let us consider the users: U_x and U_y.

If the user Ux evaluates explicitly the user U_y then the function WE_UU has a value different of 0 and the value of $WU(U_x,U_y)$ will be $WE\_UU(U_x,U_y)$.

If U_x does not make an explicit evaluation for user U_y then $WU(U_x,U_y)$ value will be the inferred value which is actually the value of $WI\_UU(U_x,U_y)$.

- we consider a function *WR(user, resource)* for every pair *(user, resource)*

WR (user, resource) value will be *WE_UR* if the user evaluates explicitly the resource, thus the value of *WE_UR* exists. Otherwise *WR* value will be the value of *WI_UR*.

Therefore, let us consider the user U_x and the resource Ry. $WR (U_x, R_y)$ value will be $WE\_UR (U_x,R_y)$ if user U_x has explicitly evaluated the resource Ry. Otherwise *WR* value will be $WI\_UR (U_x, R_y)$ if the user U_x did not evaluate the resource. This value is based on the ratings to R_y made by users which are in known list of the user U_x.

We will define the manner of computation of the implicit values introduced above.

Implicit WI_UU Value Computation

Let us consider two users U_x, U_y from the Web community. In order to define **WI_UU(U_x,U_y)** we introduce the following partial functions:

- *WIU_UU(U_x,U_y)* – its value indicates the deducted worth based on explicit evaluations made by users to each other
- *WIR_UU(U_x, U_y)* – its value signifies the deducted worth based on evaluations that users do to the same resources

Defining WIU_UU value on the basis of the explicit values

Let the users, whom we have explicit ratings from user *User₁* to be U_i, $1 \le i \le k$, be $U_1,...U_k$.

Therefore we have the definition *WE_UU (User₁, U_i)*. Also we have explicit ratings from U_i to *User₂*, so we have defined *WE_UU (U_i, User₂)* (see Figure 1).
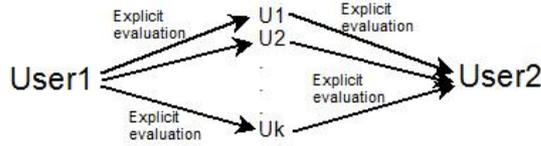

Figure 1: WI_UU computation based on explicit evaluations.

To evaluate the *WIU_UU* value we must consider which is the value of the weight corresponding to the explicit ratings.

We denote this weight with *PE (User₁, U_j)*. It represents an explicit rating weight, in our case the weight of the rating provided by *User₁*.

The value of this weight is computed as a ratio of the explicitly user established value and the sum of all explicit ratings provided by him. We will have:

$$PE(User_1, U_j) = \frac{WE\_UU(User_1, U_j)}{\sum_{i=1}^{k} WE\_UU(User_1, U_i)} \quad (1)$$

where $1 \le i \le k$, $1 \le i \le k$.

In this moment we prepare the context to compute implicit rating whom user U_x provided to U_y:

$$WIU\_UU(U_x, U_y) = \sum_{j=1}^{k} PE(U_x, U_j) * WE\_UU(U_j, U_y) \quad (2)$$

where $1 \le j \le k$.

Defining WIR_UU value on the basis of resource evaluation

The need of partial function WIR_UU when the set of users used for defining of *WIU_UU* is the empty set. This means that we do not have a set of users $U_1, .., U_k$ whom we have explicit ratings from *User₁* to U_i, $1 \le i \le k$ and also we do not have explicit ratings from U_i to *User₂*. In this case we can obtain information on the basis of the worth of a set of resources evaluated by users. These resources are required to be evaluated by both users. Thus, on the basis of the evaluations of the same resource, one can obtain a mutual evaluation of two users.

Let us consider: U_x, U_y and the resources $R_1,...,R_n$. If there exists *WE_UR(U_x,R_i)* and *WE_UR(U_y,R_i)*, for all $1 \le i \le n$, then the value of *WIR_UU(U_x,U_y)* will exist and it will be equal with *WIR_UU(U_y,U_x)*. We define *WIR_UU (U_x,U_y)* as follows:

$$WIR\_UU(U_x, U_y) = MaxWorth - \frac{\sum_{i=1}^{n} |WE\_UR(U_x, R_i) - WE\_UR(U_y, R_i)|}{n} \quad (3)$$

where $1 \le i \le n$. The demonstration of the assertion:

$$WIR\_UU(U_x, U_y) = WIR\_UU(U_y, U_x) \quad (4)$$

is obvious. Therefore, in the case when we want to obtain *WI_UU* on the basis of resource evaluation *WI_UU* has the value of *WIR_UU (U_1, U_2)*.

Finally the worth of *WI_UU (U_1, U_2)* will be *WIU_UU (U_1, U_2)*, if defined, or *WIR_UU*, if defined, or it will be a default value fixed in the system configuration.

In a future work, we will present a mechanism to obtain a complete function *WIU_UU* without this implicit value. In addition, if we have both *user-user* and *user-resource* evaluations, then we can foresee a given priority between them.

Implicit WI_UR Value Computation

We will define the manner to obtain the worth of the implicit evaluation - **WI_UR(U_x,R_z)** – whom a user U_x provides to a resource R_z, 1<z<n, where n is the resource number of the system. We consider that the user U_x has in his known person list the following users: $U_1,...,U_k$. These users have evaluated the considered resource. This means we have defined the following relations: *WE_UU(U_x,U_i)*, $1 \le i \le k$ and also *WE_UR(U_i,R_z)*, $1 \le i \le k$

The implicit rating provide by U_x to resource R_z is represented by the proportion between: sum of the product of the rating weights of the user U_x for each user from his list and the value provided by him to

resource R_z, and the number of users (which is k in our situation)

$$WI\_UR(U_x, R_z) = \frac{\sum_{i=1}^{k} PE(U_x, U_i) * WE\_UR(U_i, R_z)}{k} \quad (5)$$

where $1 \le i \le k$. We introduce the *worth average* provided to a resource and we denote it with *WA*. The value of *WA (Resource)* represents relevant statistical average provided to a resource by all users. *WA* for a resource inside a Web community plays the same role that page rank plays in Web page evaluation. This metric is necessary in case we do not have enough trustworthy evaluators in the community.

4 ASPECTS REGARDING THE PRES BENEFITS

In this section we discuss shortly a set of consequences, due to the way the system has been modeled. We will argue our assertions through few examples and in a next paper we will give the appropriate algorithms used for these cases.

- The system assures the property to see the things prioritized the same way as similar users.
- The spammers will see more spam because the system groups the users by their preferences.

Let us consider a web community with users $U_1, \ldots, U_k$. We can consider that a new user U_x joins the community and posts a new resource - R_x.

The resource posted by U_x will be evaluated by the users from community with worth values (implicitly WE_UR(U_x,R_x)=5).

If R_x is a spam resource, it will be explicitly evaluated by users U_i which are not interested in spam resources with WE_UR(U_i,R_x)=1 or it will be explicitly evaluated by users Uj which are interested by this kind of resources with WE_UR(U_j,R_x) = 5, where $1 \le i \le k$, $1 \le j \le k$, $i \ne j$.

Also, let us consider the case when a user U_y evaluates the users U_i. Because users U_i have evaluated resource Rx with low worth than the sum $\sum_{i=1}^{k} PE(U_x, U_i) * WE\_UR(U_i, R_z)$ has a low value. Than the value of WI_UR(U_y,R_x) will be low and in this case the spam resource R_x will not be considered interesting for the user U_y.

In other case when user U_y will evaluate users U_j with worth metric with a higher value than the sum $\sum_{i=1}^{k} PE(U_x, U_i) * WE\_UR(U_i, R_z)$ has a higher value and in this case the resource R_x will be automatically consider useful for user U_y. We argue with this example one case from a set of possible use-cases. We will discuss in detail these cases and the used algorithms in our next paper.

- The resources which are relevant for the user are on top of the list of visible resources. In this moment we know that Google uses Page Rank system. The new resources, even valuable, will reach hardly on the top, because it takes long until they receive links. And worse it is the fact that if they are not on the top, they do not receive links.

Therefore there exists a very high probability that a good resource is not used.

In our system the new valuable resources appear quickly on top when they are evaluated first by an honest community member (one who tries always to evaluate correctly). If somebody over evaluate his own resource and the others rate it with low marks, the mark WI_UU will drop, therefore those who add resources are required to give right marks.

- The users will be required to do a fair evaluation.

It will not happen like in the eBay system. In this system, one assures a feedback for each user. The feedback value is obtaining from other users evaluations. One observed that the users are afraid of obtaining a negative feedback. For this reason they post positive feedbacks in a high proportion, hoping that they will obtain positive feedbacks.

- The system can be easily integrated in different Web communities.

Let us consider a real community like LinkedIn. There exist in this moment some posted announcements which offer jobs for this community only. Our system would give the possibility that this announcements to be visualized only by the users with a given profile, the announcement being not useful for other users types.

Thus our system makes it more efficient the information management that is visible to the user.

5 CONCLUSIONS

Reputation system gives people information about past activities of the other users. It can enhance an on-line interaction environment by: helping people decide who to interact, encouraging people to be more honest, discouraging those who are not responsible from participating. The actions, the behavior, the user preferences can be regarded as resources on which one can initiate interpretation and processing mechanisms. PRES system allows each user to have its own evaluation of the resources and of the other users. The proposed metrics can be used for implementation in real Web communities.

In this work we have presented the basic elements of PRES model. For the future development of the prototype we will perform a detailed analyzes of the system properties.

In a real system the resources are changing in time. This problem will be studied in our system thus foreseeing the possibility that the users can see and change the given ratings.

Another problem related to the reputation computation that will be studied is a complexity of the algorithm of performing the entire calculus in the system. The computation of *WR* and *WU* can be easily performed for a proper number of resources and users. For hundreds thousands of users and resources we need a parallel algorithm to compute periodically the *WR* and *WU* values.

REFERENCES

Amy N. Langville, Carl D. Meyer, 2006. *Google's PageRank and Beyond: The Science of Search Engine Rankings* , Princeton University Press

Hai Zhuge, *The Web Resource Space Model*, 2008, Springer.

J. Golbeck, J. Hendler. 2006. Inferring Trust Relationships in Web-Based Social Networks, *ACM Transactions on Internet Technology,* 6(4)*.*

J. Golbeck, J. Hendler. 2004. Accuracy of Metrics for Inferring Trust and Reputation in Semantic Web-based Social Networks, *Proceedings of 14th International Conference on Knowledge Engineering and Knowledge Management*, Northamptonshire, U.K.

Paolo Massa, Bobby Bhattacharjee, 2004, Using trust in recommender systems: an extol analysis, in Proceedings of iTrust 2004

O'Reilly, T., 2005. *What is Web 2.0 – Design Patterns and Business Models for the Next Generation of Software*. O'Reilly.

R. Falcone, S.Barber, L. Korba, M. Singh (Eds.), 2002, *Trust, reputation, and Security: Theories and Practice.* AAMAS 2002 International Workshop, Springer

Ross A. Malaga, 2004. Web-Based Reputation Management Systems: Problems and Suggested Solutions, Springer

L. Mui, PhD thesis: *Computational models of trust and reputation: agents, evolutionary, games and social networks*, MIT, 2002

Jennifer Golbeck, James Hendler: *Reputation network analysis for email filtering*, for the 1st Conf. on Email and Anti-Spam, 2004

T. Berners-Lee et al. (eds.), Uniform Resource Identifiers (URI): General Syntax, RFC 2396, IETF, 1998

Toby Segaran, 2007. *Programming Collective Intelligence*, O'Reilly.

Web-o-Trust effort by Russell Nelson, http://www.web-o-trust.org/.

del.icio.us. http://del.icio.us/.

dig.com. http://digg.com/.

Slashdot. http://slashdot.org/.

eBay. http://www.ebay.com/.

LinkedIn. http://www.linkedin.com

Everything2.http://everything2.com/.

Wikipedia. http://en.wikipedia.org.