7.4 development(s) – living in a virtual economy

Mashups on the Web are interesting representatives of what one may call a *virtual economy*, with a business-model that is not grounded in traditional *production* and *trade* values, but rather consists of value-added services with an indirect, albeit substantial, financial spin-off, due to recommendations and referrals. The basic mechanisms in a recommender economy are, according to Economy:

- cross sale – users who bought A also bought B
- up sale – if you buy A and B together ...

Where the principles underlying this virtual economy have definitely proven their value in first (ordinary) life economy, what are the chances that these principles are also valid, for example, in Second Life?

According to the media companies selling their services to assist the creation of presence in Second Life, there are plenty *New Media Opportunities In The Online World Second Life*[1], to a possibly even greater extent, as they boldly claim, as in what they call *the predecessor of Second Life, the World Wide Web.*

To assess the role web services, including semantic web services, may play in Second Life, it seems worthwhile to investigate to what extent web services can be deployed to deliver more traditional media, such as *digital TV*. To support the business model of digital TV, which in outline may be summarized as *providing additional information*, *game playing* and *video on demand*, with an appropriate payment scheme, DTV argue in favor of the use of a SOA (Service Oriented Architecture), to allow for a unified, well-maintainable approach in managing collections of audio-visual objects. Such services would include metadata annotation, water-marking for intellectual property protection, and search facilities for the end-user. Framework even propose to wrap each individual audio-visual object in a (semantic) web service and provide compound services based on semantic web technologies such as OWL-S[2] (OWL-based Web Service Ontology) and WSMO[3] (Web Service Modelling Ontology) using semi-automatic methods together with appropriate semantic web tools[4], for the description and composition of such services. Obviously, there is a great technical challenge in creating such self adjusting service environments.

With respect to the application of web services in Second Life, however, a far more modest aim, it seems that nevertheless the business model associated with the delivery of media items through digital TV channels may profitably be used in Second Life, and also the idea of wrapping media items in web services has in some way an immediate appeal.

In Recommend, we introduced the notion of *serial recommender*, which generates guided tours in 3D digital dossier(s) based on (expert) user tracking. See section 6.4. To incrementally refine such tours for individual users, we used

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[1] www.youtube.com/watch?v=8NOHRJB9uyI
[2] www.daml.org/services/owl-s/
[3] www.wsmo.org/
[4] composing-the-semantic-web.blogspot.com/

a behavioral model originally developed in Privacy. This model distinguishes between:

U = *user*
I = *item*
B = *behavior*
R = *recommendation*
F = *feature*

and allows for characterizing observations (from which implicit ratings can be derived) and recommendations, as follows:

- observations – $U \times I \times B$
- recommendations – $U \times I$

In a centralized approach the mapping $U \times I \times B \rightarrow U \times I$ provides recommendations from observations, either directly by applying the $U \times I \rightarrow I \times I$ mapping, or indirectly by the mapping $U \times I \rightarrow U \times U \rightarrow I \times I$, which uses an intermediate matrix (or product space) $U \times U$ indicating the (preference) relation between users or user-groups. Taken as a matrix, we may fill the entries with distance or weight values. Otherwise, when we use product spaces, we need to provide an additional mapping to the range of $[0, 1]$, where distance can be taken as the dual of weight, that is $d = 1 - w$.

In a decentralized approach, Privacy argue that it is better to use the actual features of the items, and proceed from a mapping $I \times F \rightarrow U \times I \times R$. Updating preferences is then a matter of applying a $I \times B \rightarrow I \times F$ mapping, by analyzing which features are considered important.

For example, observing that a user spends a particular amount of time and gives a rating r, we may apply this rating to all features of the item, which will indirectly influence the rating of items with similar features.

B = [time = 20sec, rating = r]
F = [artist = rembrandt, topic = portrait]
R = [artist(rembrandt) = r, topic(portrait) = r]

Privacy observe that B and R need not to be standardized, however F must be a common or shared feature space to allow for the generalization of the rating of particular items to similar items.

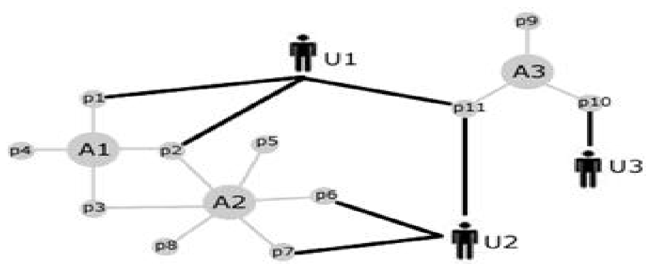
With reference to the CHIP project, mentioned in the previous section, we may model a collection of artworks by (partially) enumerating their properties, as indicated below:

$A = [\ p_1, p_2, \ldots\ ]$
where $p_k = [\ f_1 = v_1,\ f_2 = v_2,\ \ldots\ ]$

with as an example

$A_{nightwatch}$ = [artist=rembrandt, topic=group]
$A_{guernica}$ = [artist=picasso, topic=group]

Then we can see how preferences may be shared among users, by taking into account the (preference) value adhered to artworks or individual properties, as illustrated in the figure below.



users, artworks and properties

[1]

As a note, to avoid misunderstanding, Picasso's Guernica is not part of the collection of the Rijksmuseum, and does as such not figure in the CHIP studies. The example is taken, however, to clarify some properties of metrics on art collections, to be discussed in the next section.

To measure similarity, in information retrieval commonly a distance measure is used. In mathematical terms a distance function $d : X \rightarrow [0, 1]$ is distance measure if:

$$d(x, y) = d(y, x)$$
$$d(x, y) \leqslant d(x, z) + d(z, y)$$
$$d(x, x) = 0$$

From an abstract perspective, measuring the distance between artworks, grouped according to some preference criterium, may give insight in along which dimesnion the grouping is done, or in other words what attributes have preference over others. When we consider the artworks

a_1 = [artist = rembrandt, topic = self-portrait]
a_2 = [artist = rembrandt, name = nightwatch]
a_3 = [artist = picasso, topic = self-portrait]
a_4 = [artist = picasso, name = guernica]

we may, in an abstract fashion, deduce that if $d(a_1, a_2) < d(a_1, a_3)$ then $r(topic) < r(artist)$, however if $d(a_1, a_3) < d(a_1, a_2)$ the reverse is true, that is then $r(artist) < r(topic)$. Somehow, it seems unlikely that a_2 and a_4 will be grouped together, since even though their topic may considered to be related, the aesthetic impact of these works is quite different, where *self portrets* as a genre practiced over the centuries indeed seem to form a 'logical' category. Note that we may also express this as $w(artist) < w(topic)$ if we choose to apply weights to existing ratings, and then use the observation that if $d(a_1, a_3) < d(a_1, a_2)$ then $w(artist) < w(topic)$ to generate a guided tour in which a_3 precedes a_2.

For serial recommenders, that provide the user with a sequence of items $\ldots, s_{n-1}, s_n, \ldots$, and for s_n possibly alternatives $a_1, a_2, \ldots$, we may adapt the (implied) preference of the user, when the user chooses to select alternative a_k instead of accepting s_n as provided by the recommender, to adjust the weight of the items involved, or features thereof, by taking into account an additional constraint on the distance measure. Differently put, when we denote by $s_{n-1} \mapsto s_n/[a_1, a_2, \ldots]$ the presentation of item s_n with as possible alternatives $a_1, a_2, \ldots$, we know that $d(s_{n-1}, a_k) < d(s_{n-1}, s_n)$ for some k, if the user chooses for a_k In other words, from observation B_n we can deduce R_n:

B_n = [time = 20sec, forward = a_k]
F_n = [artist = rembrandt, topic = portrait]
R_n = [$d(s_n, a_k) < d(s_n, s_{n+1})$]

leaving, at this moment, the feature vector F_n unaffected. Together, the collection of recommendations, or more properly revisions R_i over a sequence S, can be solved as a system of linear equations to adapt or revise the (original) ratings. Hence, we might be tempted to speak of the $R4$ framework, *rate, recommend, regret, revise.* However, we prefer to take into account the cyclic/incremental nature of recommending, which allows us to identify revision with rating.

measures for feedback discrepancey So far, we have not indicated how to process user feedback, given during the presentation of a guided tour, which in the simple case merely consists of selecting a possible alternative. Before looking in more detail at how to process user feedback, let us consider the dimensions involved in the rating of items, determining the eventual recommendation of these or similar items. In outline, the dimensions involved in rating are:

dimension(s)

- positive vs negative
- individual vs community/collaborative
- feature-based vs item-based

Surprisingly, in User we found that negative ratings of artworks had no predictive value for an explicit rating of (preferences for) the categories and properties of artworks. Leaving the dimension *individual vs community/collaborative* aside, since this falls outside of the scope of this paper, we face the question of how to revise feature ratings on the basis of preferences stated for items, which occurs (implicitly) when the user selects an alternative for an item presented in a guided tour, from a finite collection of alternatives.

A very straightforward way is to ask explicitly what properties influence the decision. More precisely, we may ask the user why a particular alternative is selected, and let the user indicate what s/he likes about the selected alternative and dislikes about the item presented by the recommender. It is our expectation, which must however yet be verified, that negative preferences do have an impact on the explicit characterization of the (positive and negative) preferences for general artwork categories and properties, since presenting a guided tour, as an organized collection of items, is in some sense more directly related to user goals (or educational targets) than the presentation of an unorganized collection of individual items. Cf. Hybrid.

So let's look at $s_{n-1} \mapsto s_n/[a_1, a_2, \ldots]$ expressing alternative selection options $a_1, a_2, \ldots$ at s_n in sequence $S = \ldots, s_{n-1}, s_n$. We may distinguish between the following interpretations, or revisions:

interpretation(s)

- neutral interpretation – use $d(s_n, a_k) < d(s_n, s_{n+1})$
- positive interpretation – increase $w(\mathit{feature}(a_k))$
- negative interpretation – decrease $w(\mathit{feature}(s_{n+1}))$

How to actually deal with the revision of weights for individual features is, again, beyond the scope of this paper. We refer however to OO, where we used feature vectors to find (dis)similarity between musical fragments, and to Features, on which our previous work was based, where a feature grammar is introduced that characterizes an object or item as a hierarchical structure, that may be used to access and manipulate the component-attributes of an item.