2nd IEEE International Workshop on Advanced Information Systems for Enterprises

IWAISE'12

Recommendation Of Learning Resources And Users Using An Aggregation-Based Approach

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Introduction

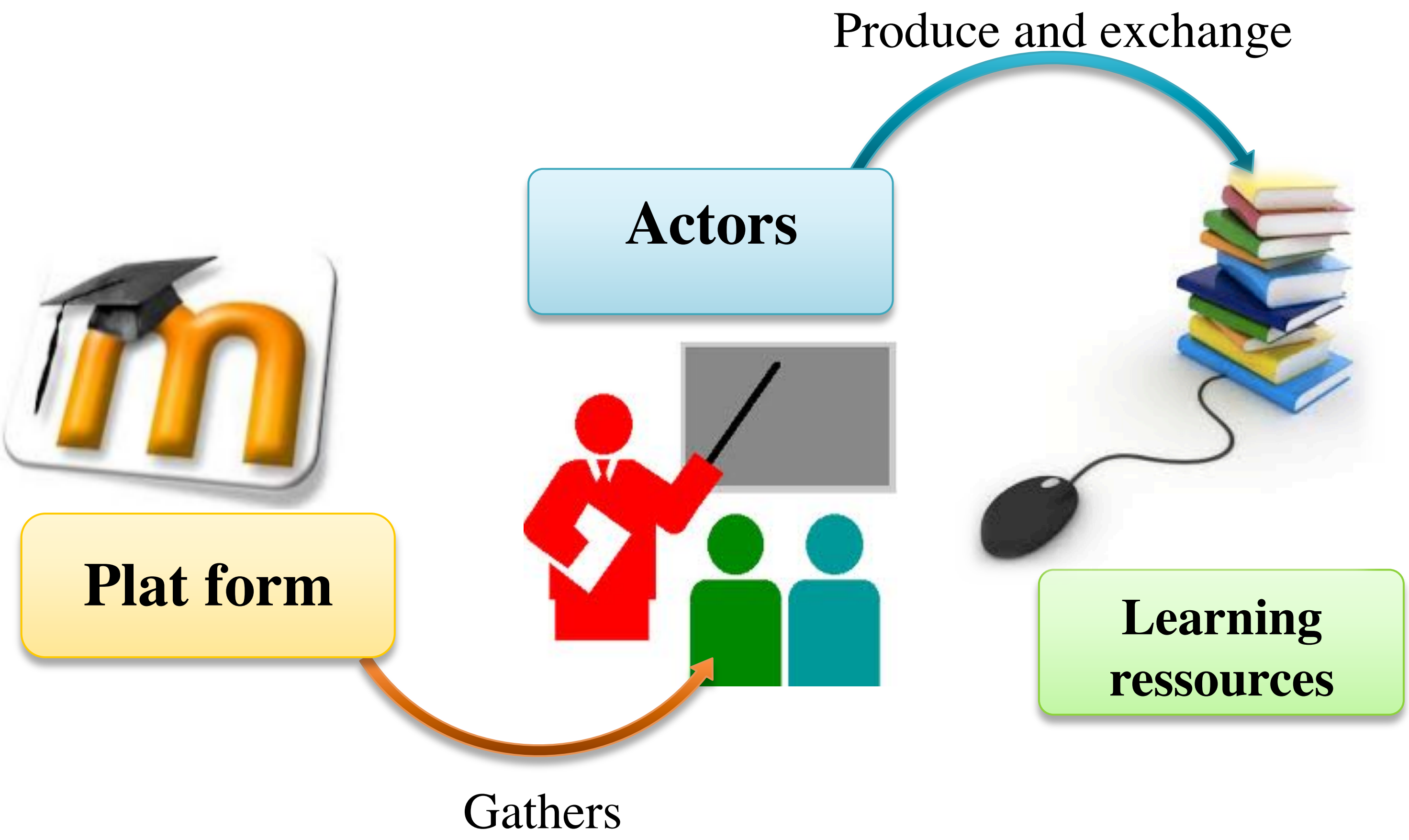
The Application of information and communication technologies in education led to the creation of new form of learning called **e-learning**.

Introduction

The European Commission, defined e-learning as [CUEU01]: « *The utilization of new multimedia technologies and the Internet to improve the quality of learning by* ***facilitating access to resources*** *and services, as well as* ***exchanges and distant collaboration*** ».

Introduction

Some basic concepts of e-learning :



Problematic

Example: Merlot (www.merlot.org)

2009

2012

70.000 membres

107.073 membres

20.000 resources

38.412 resources

Proplematic

- How the actors of e-learning can find the adequate learning resources according to their needs and profiles. In this large number of available resources that increasing more and more?

- In order to enhance collaboration between actors, there is a need for finding other actors with similar profiles (interests,preferences, needs...). How can we do it in this voliminous number of actors?

- Introduction
- Recommender System
- Recommendation in e-learning
- Our approach of recommendation
- Conclusion and Perspectives

Recommender System

The definition given by **Robin Burke** [BURK02]: « *The recommender system is any system that produces individualized recommendations as output or has the effect of guiding the user in a personalized way to interesting or useful objects in a large space of possible options* ».

Recommender System

Two types of recommender systems:

- **Content based Filtering (CBF)**
- **Collaborative Filtering (CF)**

Content based Filtering (CBF)

The content-based filtering system selects items based on the correlation between the content of the items, and the user's preferences [ZAIE10].

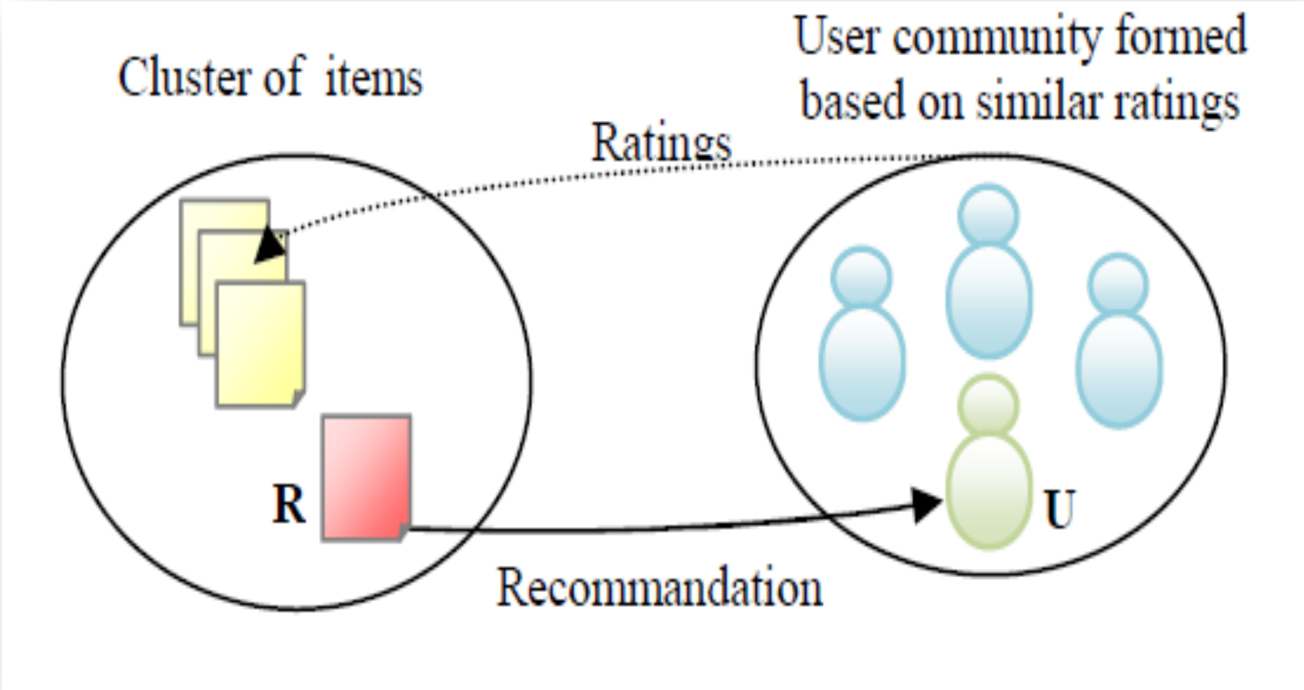
A major disadvantage of content-based methods is that they require analyzing the content of documents, which is computationally expensive and even impossible to perform on multimedia items which do not contain text.

Collaborative Filtering (CF)

CF is considered as one of the most successful approaches for building recommender systems. It uses the known preferences of a group of users to make recommendations or predictions of the unknown preferences for other users [XSUM09].

Collaborative Filtering (CF)

The Principe of Collaborative Filtering



Filtrage Collaboratif (FC)

Unlike CBF; CF ignores the form and the content of items and can therefore also be applied to non-textual items. But it suffers from some disadvantages:

- First-Rater problem;
- Sparsity problem;
- No preferences.

Recommendation in E-learning

System	The technique of recommendation	Recommended objet(s)
Alterred Vista system [RECK02]	CF	-Learning resources - actors
RACOFI [ANDE03]	Hybrid Recommendation	-Learning resources
QSIA [RAFA04]	CF	-Learning resources
CYCLADES [AVAN05]	CF	-Learning resources
An ecolving e-learning system [TANG05]	Hybrid Recommendation	-Learning resources
ReMashed[DRAC09]	Hybrid Recommendation	-Services

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Our approach of recommendation

Namely:

- Roles and interests of actors;
- Meta-data representing learning resources.

Our approach of recommendation

Before detailing how our system benefits from these characteristics, we first describe its several Concepts:

- **Users**: represents the actors of e-learning;
- **Items**: represents learning resources;
- **Profile**: a description for each user;
- **Community**: group of linked users based on some specific criteria;
- **Recommendation**: a list of N items where the target user will like the most;

Our approach of recommendation

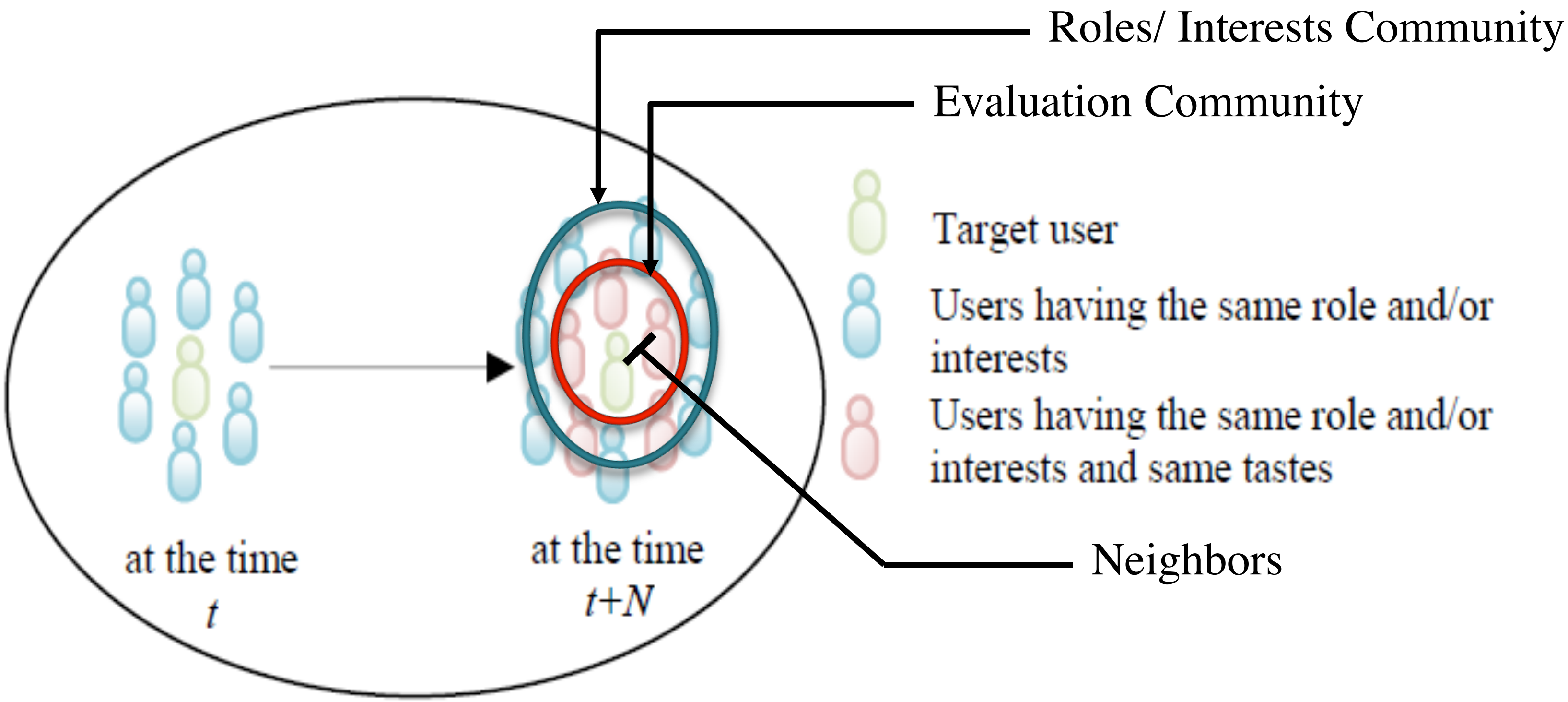
Before detailing how our system benefits from these characteristics, we first describe its several Concepts:

- **Favorite collection**: learning resources with user's previous likings chosen by him;
- **Prediction**: a numerical value, expressing the predicted likeliness of an item the user hasn't expressed his opinion about;
- **Contact list**: a collection of user's with a similar tastes selected by the target user.

Roles/Interests

In a classic CF we have simple communities based on similar evaluations. However, the problem is when a new user is introduced; the system couldn't give any recommendation for him (*no preferences problem)*. As a solution to this problem, we propose using role and interest

Roles/Interests



Roles/Interests

Calculate the similarity (*Pearson correlation coefficient Similarity*):

$$Sim(u,v) = \frac{\sum_{i \in Iuv}(R_{u,i} - \bar{R}_u)(R_{v,i} - \bar{R}_v)}{\sqrt{\sum_{i \in Iuv}(R_{u,i} - \bar{R}_u)^2}\, l \sqrt{\sum_{i \in Iuv}(R_{v,i} - \bar{R}_v)^2}}$$

Where:

-$Sim(u,v)$: represents the similarity between user

-I_{uv}($I_{uv} = I(u) \cap I(v)$) :means the item set rated simultaneously by user u and user v,

-$R_{u,i}$, $R_{v,i}$: are the scores of item i rated by user u and v respectively,

- $\bar{R}_u$, $\bar{R}_v$: represent the average scores of user u and v for their rated items respectively.

Roles/Interests

Calculate the prediction:

$$Pred(U_i, I_j) = \alpha_1(\bar{R}_{C,i}) + \alpha_2(\bar{R}_{E,i}) + \alpha_3(\bar{R}_{I,i}) + \alpha_4(\bar{R}_{R,i})$$

Where:

- $Pred(U_i, I_j)$: is prediction of the user Ui pour l'item Ij
- $\alpha_{1..4}$: are coefficients,

$\bar{R}_{C,i}$,$\bar{R}_{E,i}$, $\bar{R}_{I,i}$, $\bar{R}_{R,i}$ are respectively the average ratings of contact list, Evaluation community, Interest community, Role community. (where $C \cap E \cap I \cap R = \emptyset$).

Algorithm I

Begin

Step1 Build the profile of the User A

Step2 Extract the Role and Interests of A (role R, Interests I)

Step3 Aggregate A with other users having as Role R and/or interests I

Step4 Calculate the predictions of learning resources

Step5 Send a preliminary Recommendation for A

Step6 Save the interactions and ratings of A

Step7 Compute similarity between A and other members of his community of role/interest

Step8 Update the position of A, add A in an Evaluate Community EC

Step9 Calculate learning resources predictions

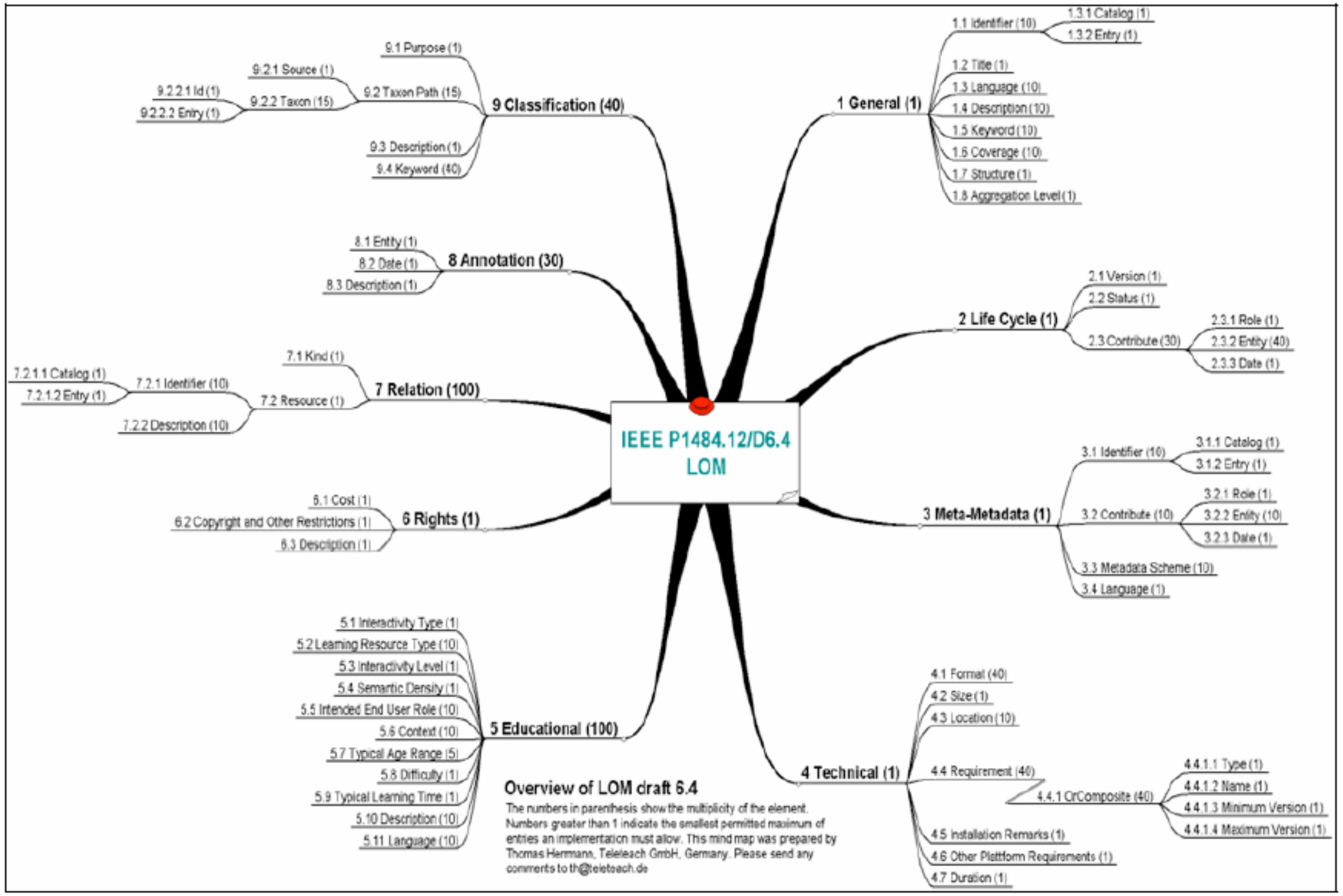
Step10 Recommend the N more predicted learning resources and users having the same tastes of A

End

Meta-data describing resources

Example IEEE proposes Learning Meta Data Object (LOM).

S



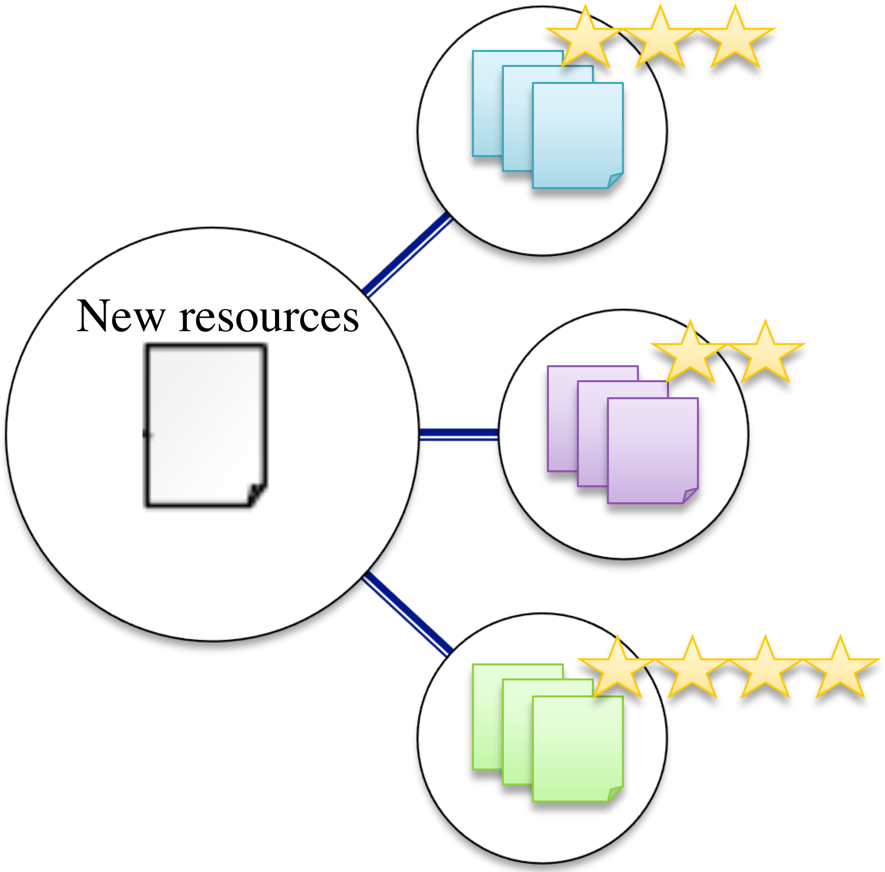
a

Meta-data describing resources

Example of Dublin Core Metadata Initiative (DCMI).

Elément	Description
Title	A name given to the resource
Creator	An entity primarily responsible for making the resource.
Subject	The topic of the resource.
Description	An account of the resource.
Publisher	An entity responsible for making the resource available.
Contributor	An entity responsible for making contributions to the resource.
Date	A point or period of time associated with an event in the lifecycle of the resource
Type	The nature or genre of the resource.
Format	An unambiguous reference to the resource within a given context.
…	…

Meta-data describing resources



"if the user liked these resources he will like this one"

Meta-data describing resources

Calculate the similarity (Jaccard similarity coefficient):

$$sim(i,j) = \frac{|i \cap j|}{|i \cup j|}$$

Where:
-i∈(Set of favorite collections),
-j is the new item.

Algorithm II

Begin

A: user

Step1 extract the meta-data MD of the new Item R

Step2 **while** (a set of favorite collection$\neq \varnothing$ or not exist a similar Item) **do**

{

Calculate the similarity between MD with the meta-data of resources in the favorite collection of A

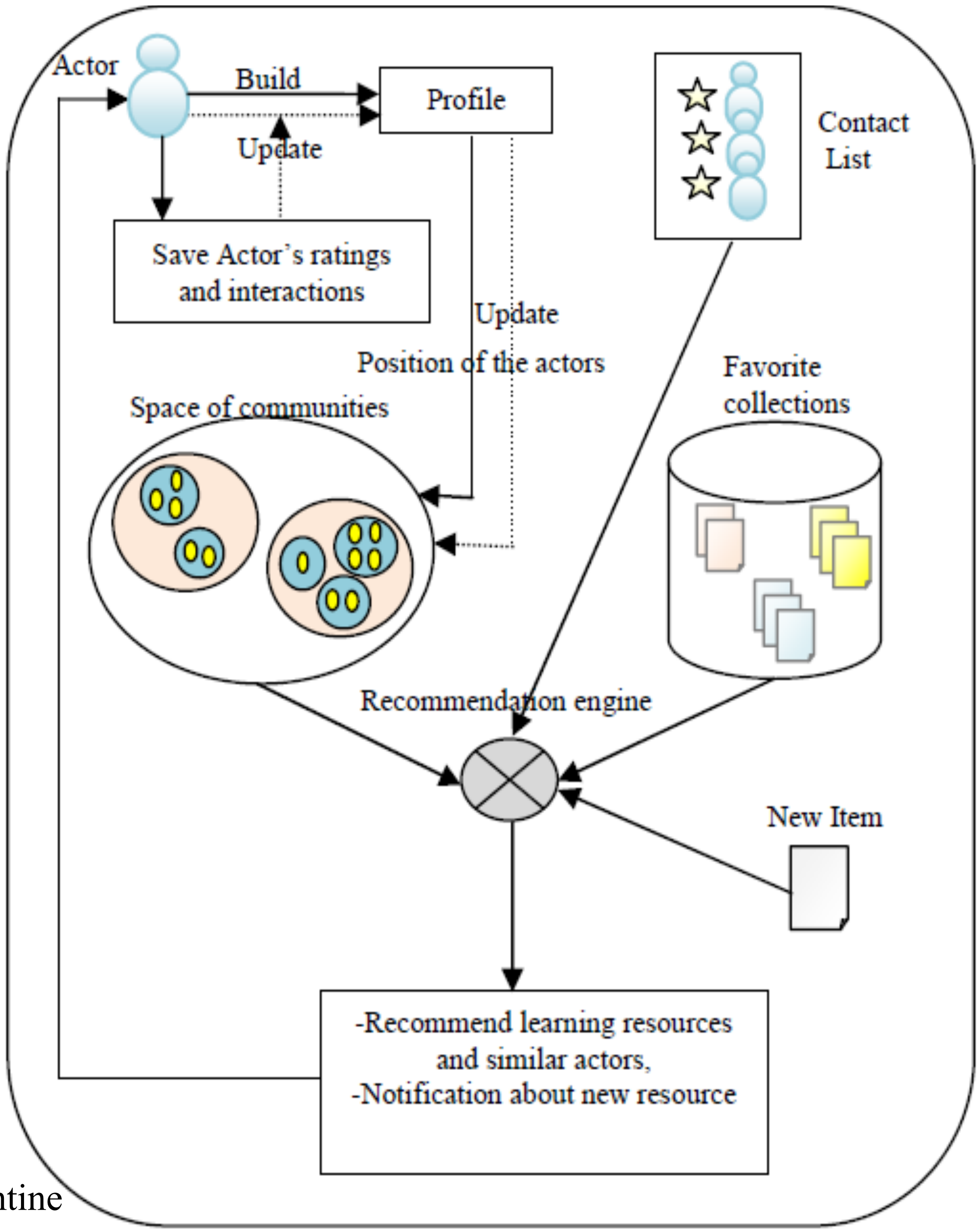
}

Step3 ***if*** (exist similar item) ***then***

{

Send notification about R for A

End


Actor
Build
Profile
Update
Save Actor's ratings and interactions
Contact List
Update
Position of the actors
Space of communities
Favorite collections
Recommendation engine
New Item
-Recommend learning resources and similar actors,
-Notification about new resource

Case study

Users	**Roles**	**Interests**	**Ratings about I**
A	Learner	DB	?
U_1	Learner	IA	Dislike
U_2	Teacher	Algorithms	Like
U_3	Learner	DB	Like
U_4	Tutor	IA	Dislike
U_5	Teacher	DB	Like

We compare the behavior of our system with a system based only on collaborative filtering.

We consider:

CR/I: Communities of roles and/or Interests.

CE: Communities of evaluation.

Case study

COLLABORATIVE FILTERING SYSTEM VS OUR RECOMMENDER SYSTEM

Events	CF system	Our system	Description
	The communities are based on mono-criterion (simple communities) -C1 (U_1,U_4) -C2 (U_2, U_3,U_5)	The communities are based on multi-criterion (aggregated communities) -C1$_{R/I}$(C_{E1} (U_1,U_4) , C_{E2} (U_3)) -C2$_{R/I}$(C_E (U_2,U_5)) -C3$_{R/I}$(C_{E1} (U_1), C_{E2} (U_3, U_5))	Unlike our system the CF system didn't exploit the two notions of role and interest
Coming of new actor A	We have any idea about the preferences of A so he will not be affected to any community	$C_{R/I}$(A,U_1 ,U_3 ,U_5)	Our system executes an initial recommendation and it suggests I for A(because it's appreciated by U_3 and U_5)

Case study

COLLABORATIVE FILTERING SYSTEM VS OUR RECOMMENDER SYSTEM

Events	CF system	Our system	Description
A like the item I		$C_{R/I}(C_{E1}(U_1)$, $C_{E2}(\ (A,U_3\ ,U_5))$ we recommend U_3 ,$U_5$for A and he has the choice to add him in his contact list and he is free also to add I in his favorite collection	Our system will execute another recommendation of items (in this time it exploits the ratings of A)
The actor X adds a new item NI	NI will not be recommend as we have any ratings about it	Calculates the similarity between metadata of NI and the other ones of each item from the actor's favorite collections	If the similarity exist our system will send a notification for the actor about the addition of NI

Introduction

Recommender System

Recommendation in e-learning

Our approach of recommendation

Conclusion and Perspectives

Conclusion & Perspectives

- We discussed the problem of e-learning actors, to find and share learning resources of various types and huge quantity.

- The solution to solve this problem is to use a recommender system.

- The most appropriate method to this context is the technique of CF although it suffers from some limitations.

- Therefore, we have presented how we use the notions of aggregation and metadata description to minimize some disadvantages of this technique.

Conclusion & Perspectives

We envisage to enrich the proposed approach by:

- Developing a prototype in order to test and evaluate the recommender systemd;
- Improving user's recommendation by adding the RDF vocabulary FOAF (Friend of a Friend), notion of activity;
- Adding a content layer to solve the problem of cold start which will switch us from a collaborative approach to a hybrid one.

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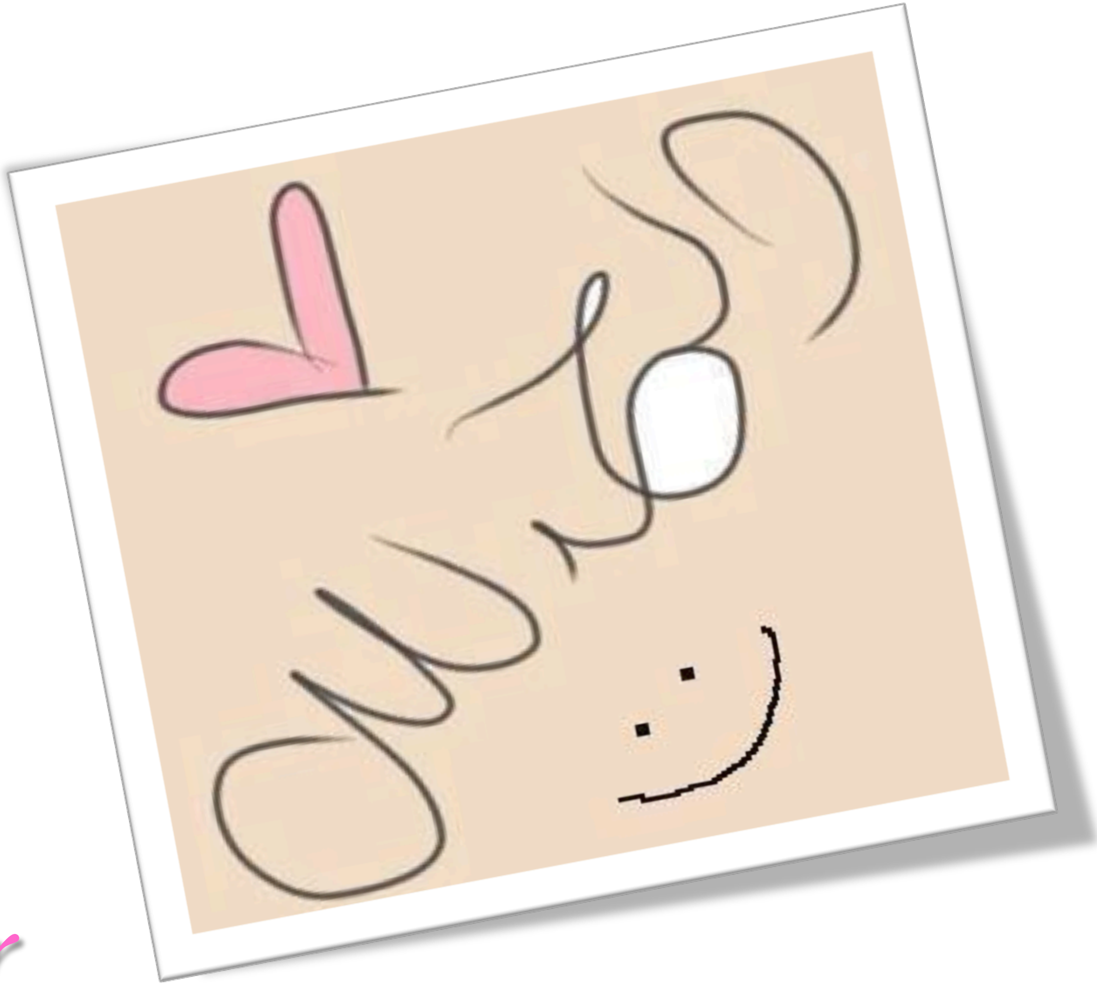

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