# Workshop eliciting Adaptive Sequences for Learning (WeASeL)

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Optimizing Recommendation in Collaborative E-Learning by Exploring DBpedia and Association Rules

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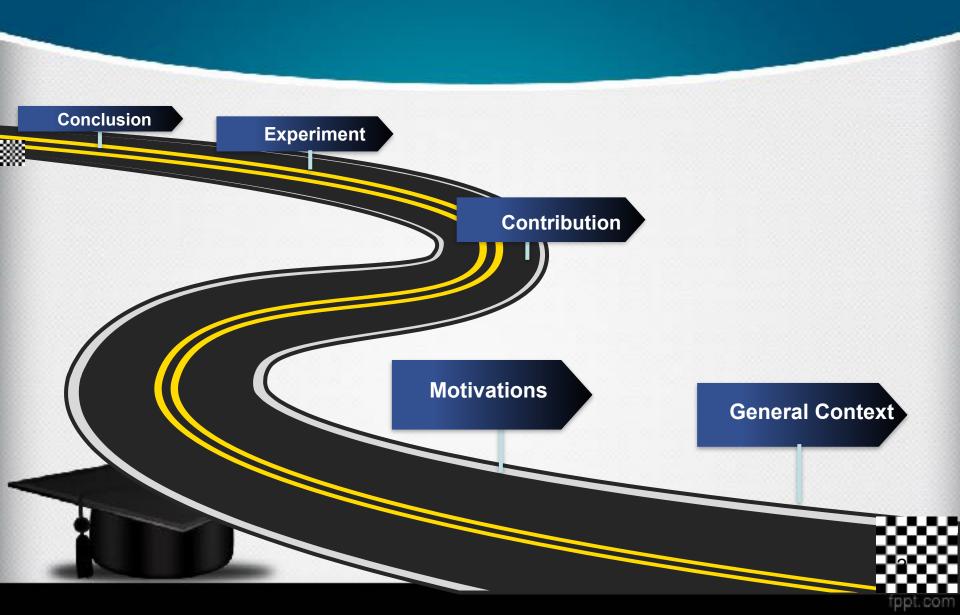
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**ITS 2018** 

## Work plan



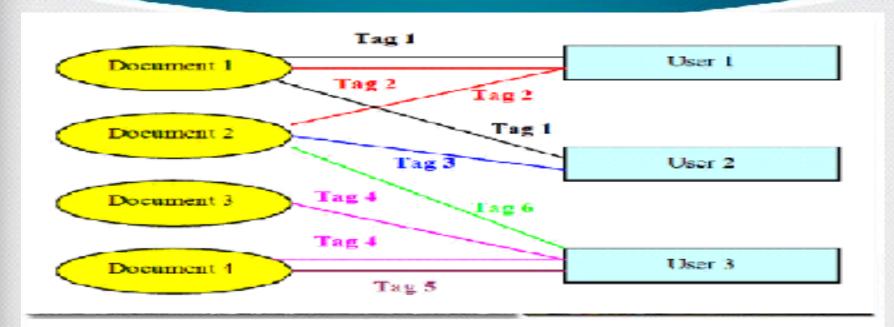
#### **General Context: Social Web**



#### **General Context: Collaborative E-learning**



#### **General Context: Folksonomies**



Indexing systems produced within internet communities



#### **General Context:**

#### **Recommendation and Collaborative E-learning**



suggest items: movies, music or products by analyzing what the users with similar tastes have chosen in the past





#### Issues in Folksonomies



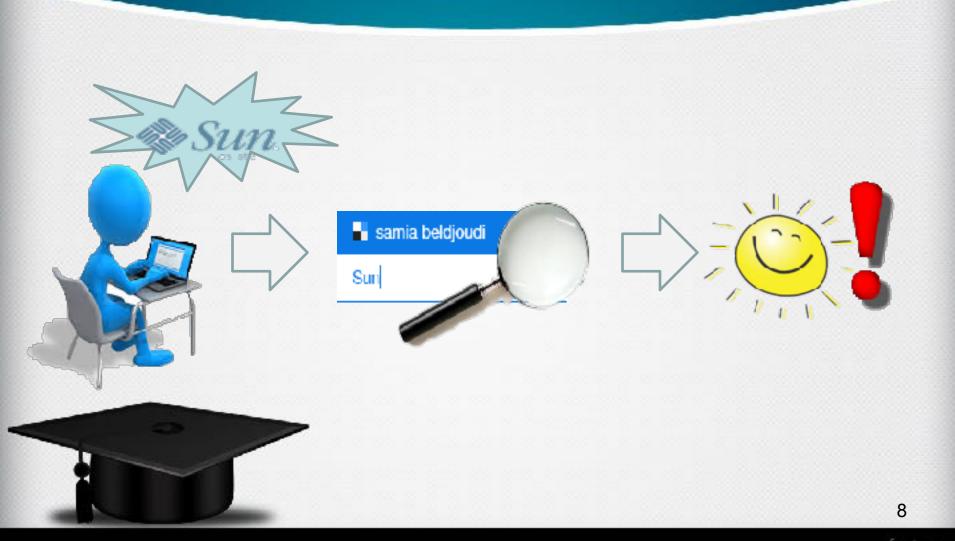
• Tag ambiguity (Polysemy: many sense):







## Example



# Recommender system issue: Diversity and Novelty



 Accuracy vs Diversity and Novelty in Recommendation:





## Linked Open Data (LOD)







#### **Research Question**



How using LOD to improve recommendation when searching personalized and relevant resources within social E-learning applications?



#### **Main Contributions**



Contribution



Reduce tag ambiguity problem in recommendation

Using LOD to ensure diversity and novelty in recommendation

### Approach description

Formally:

a folksonomy is a tuple F = <L, T, R, A>

L: learners

T: tags

R: resources

A: the relationships between the three

preceding elements, i.e.  $A \subseteq U \times T \times R$ 





### Approach description

- → Extacting 3 Social networks:
- ✓ network relating tags and users,
- √ network relating tags and resources
- ✓ network relating users and resources.

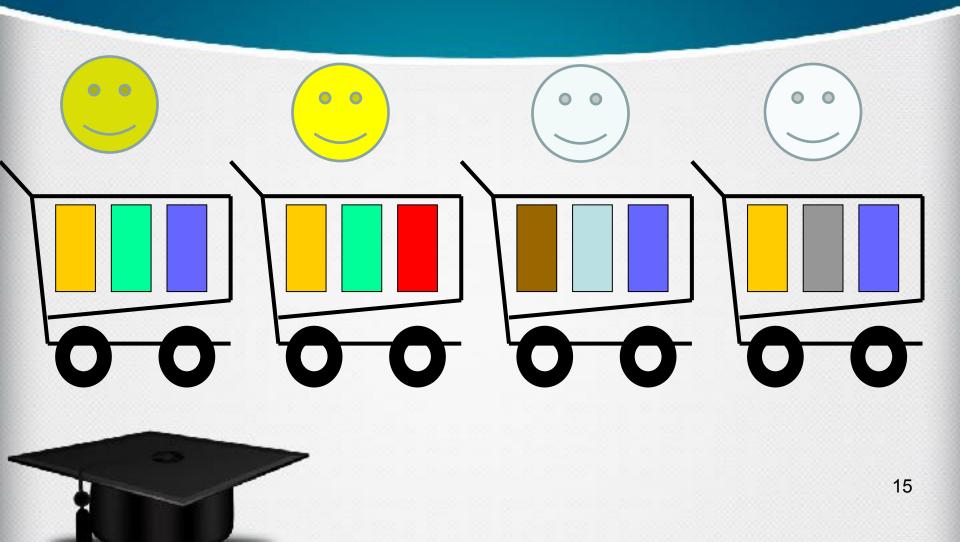


- → We represent these social networks by three matrices LT, RT, RL:
- $\circ$  LT = [X<sub>ij</sub>] where : X<sub>ij</sub>
- $\circ$  RT = [Y<sub>ii</sub>] where: Y<sub>ii</sub>

$$RL = [Z_{ij}]$$
 where:  $Z_{ij}$ 

```
 = \begin{cases} 1 \text{ if } \exists \ r \in \mathbb{R}, < uj, ti, r > \in \mathbb{A} \\ 0 \text{ otherwise} \end{cases} 
 = \begin{cases} 1 \text{ if } \exists \ u \in \mathbb{U}, < u, ti, rj > \in \mathbb{A} \\ 0 \text{ otherwise} \end{cases} 
 = \begin{cases} 1 \text{ if } \exists \ t \in \mathbb{T}, < ui, t, rj > \in \mathbb{A} \\ 0 \text{ otherwise} \end{cases}
```

#### **Association Rules**



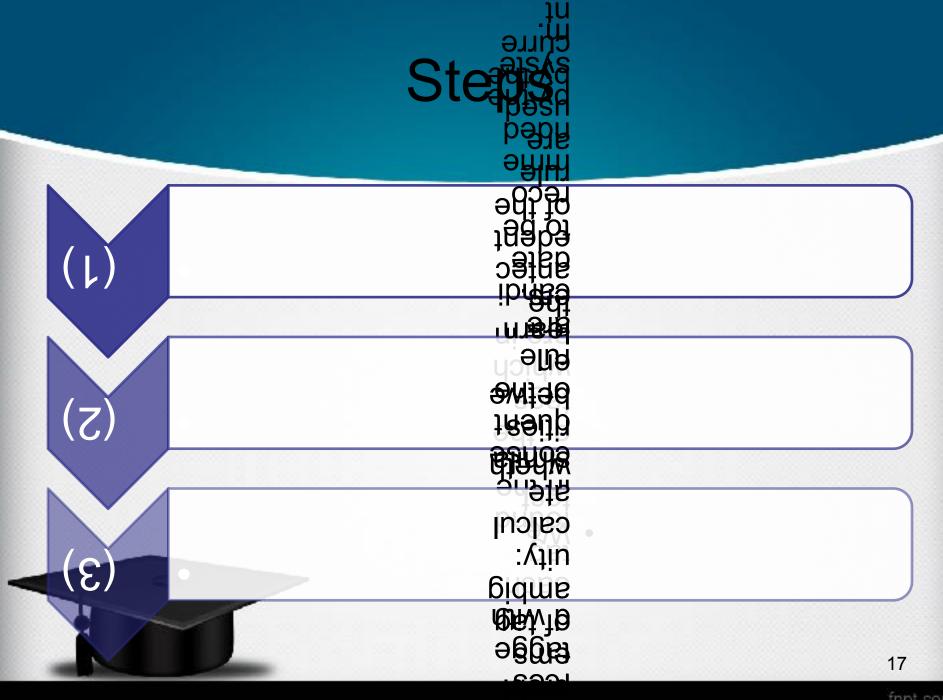
#### Associations Rules and Folksonomies

Transaction-id → Learner
Transaction items → tags used by the

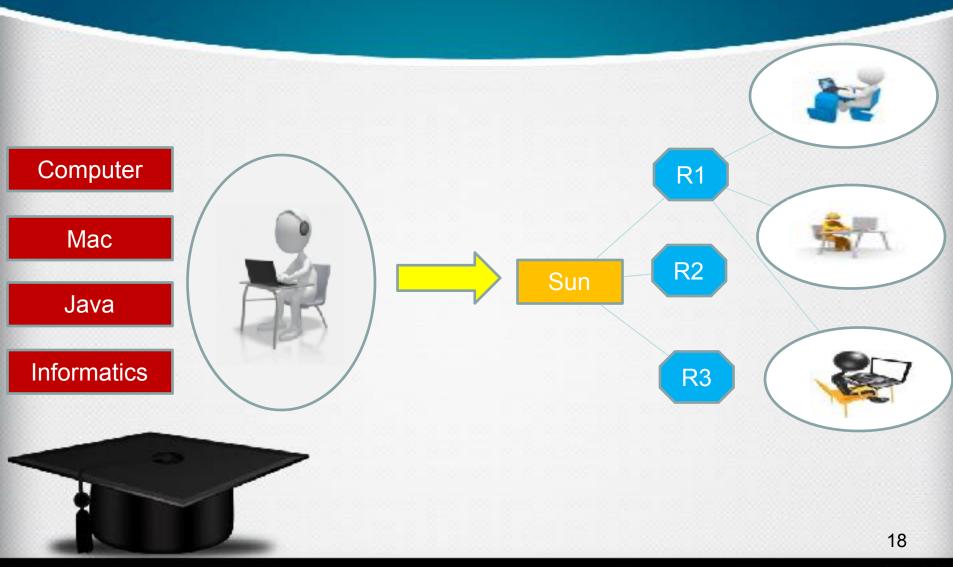
Learner (transaction-id)	Tags (itemsets)		
L1	Software, Java		
L2	Software,		
L3	Java,,Software		
L4	Java		
L5	Java,,Software		



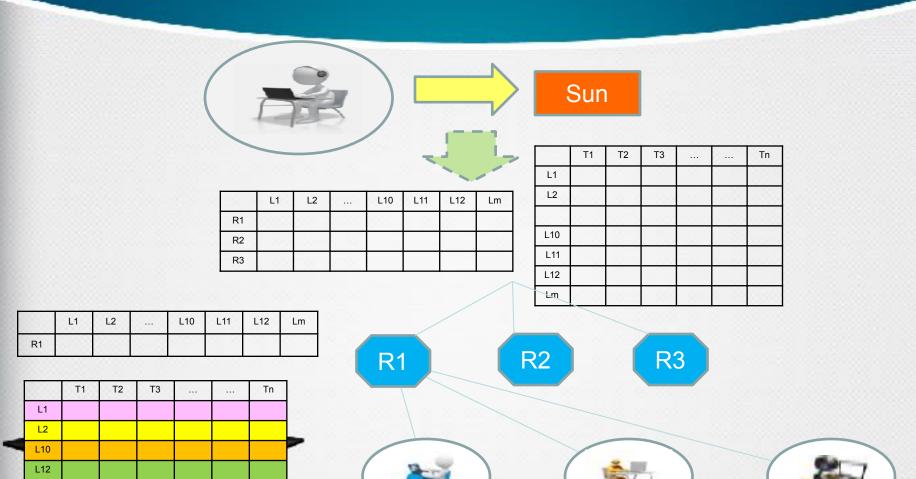
**Software** ⇒ **Java** 



## Example



## Example

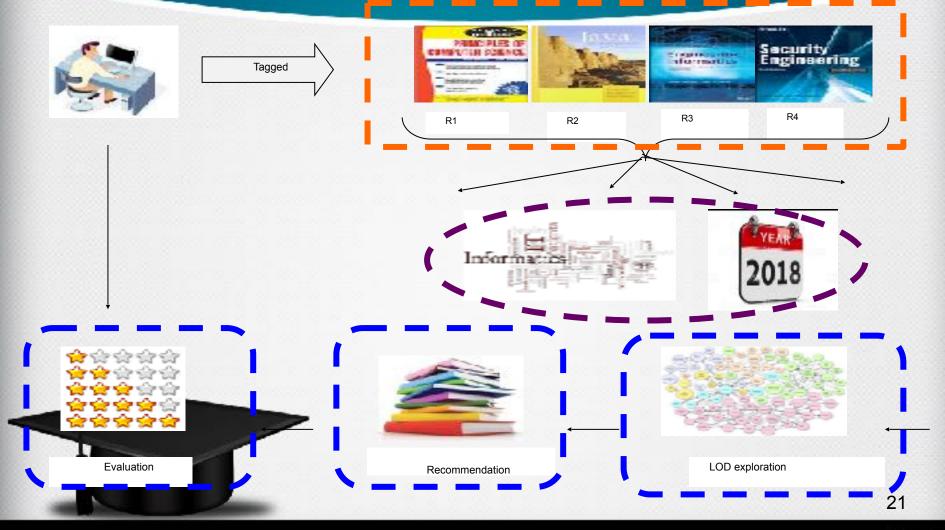


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## Diversity in Recommendation

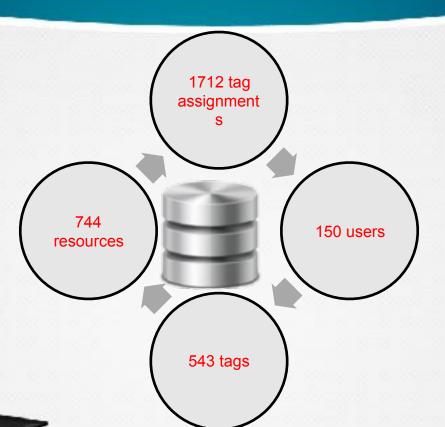


# LOD exploration to insure diversity and novelty



#### Del.icio.us database

120 association rules (support= 0.5 and confidence = 0.6.



computer ⇒
programming:
60% of the
users using the
tag "computer"
also use the tag
"programming".



#### **Evaluation Methodology**



#### **Experimental Results**

Precision	Recall	F1	Diversity	Novelty
0.78	0.71	0.74	0.76	1.2

#### Deviation value:

Precision	Recall	F1	Diversity	Novelty
0.15	0.09	0.1	0.2	0.34

The averages are very promising for the community in general → the small values of standard deviations indicate that the metrics are also promising for each user individually.

#### Conclusion











#### Future work

 Ant Colony Optimization (ACO) Algorithm

**Event detection** 





#### Thanks...



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