Recommending Learning Resources Beyond Content

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Introduction

European schools face an ever more demanding situation: despite the more sophisticated technological tools at its disposal, education practice is in general not very motivating for present-day students. Also, use Smart educational services in future classroom will become usual. The **EC FP7 iTEC Project** aims to face this situation by defining and developing new engaging scenarios for learning in future classrooms. In this frame, we propose a **Knowledge Based System (KBS)**:

- It aimed to allow teachers **to make up lesson plans** from learning activities
- It **provides recommendations** on different types of resources: applications, devices, people, and events
- It takes into account the **specific requirements** of the learning activities, together with any other information

A recommendation system for educational resources

Traditionally, users of recommendation systems provide rating for some items, and the system uses these ratings for the items no yet assessed.
TEL recommenders need to consider a learning context:

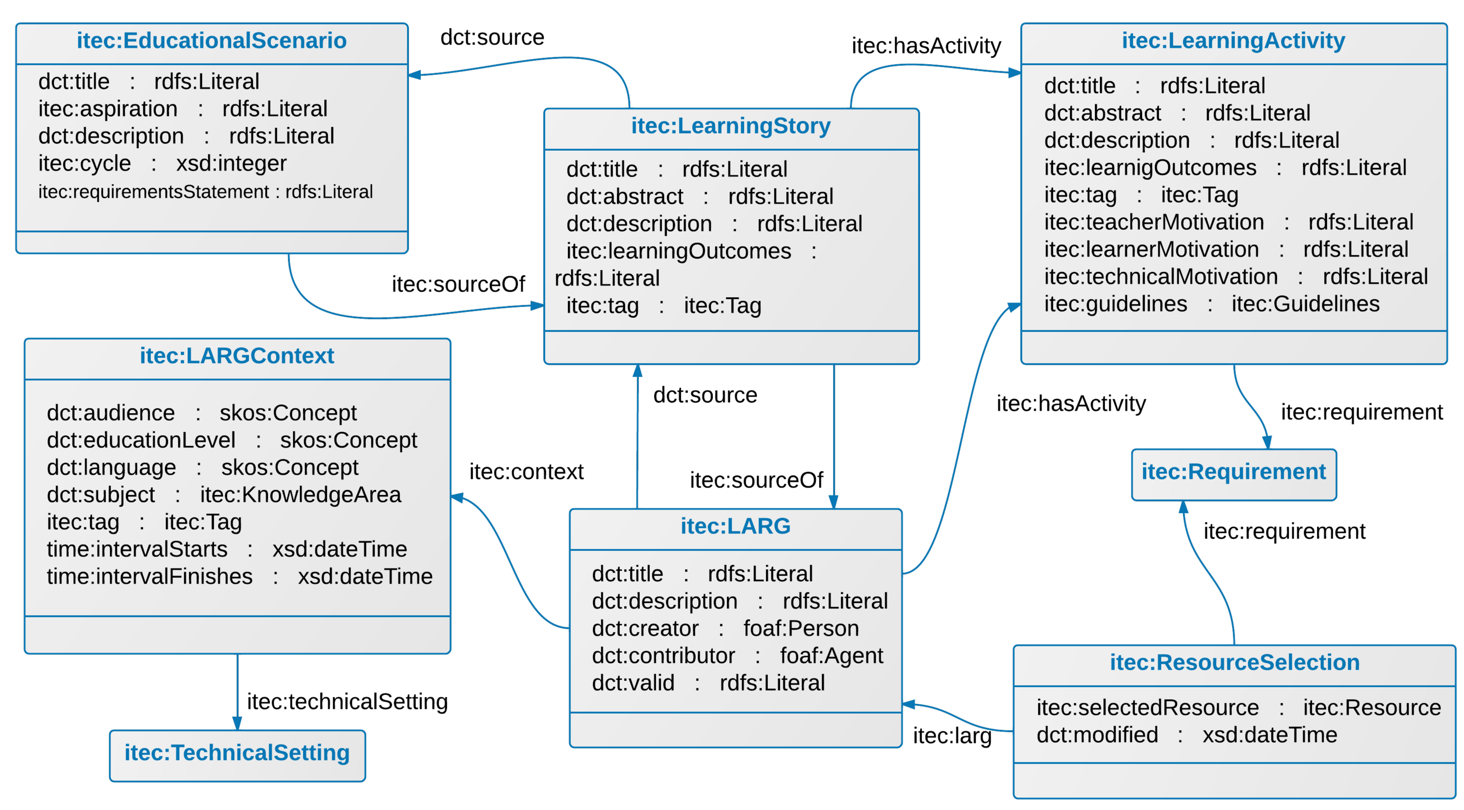
- They need to take into account several factors
  → **Multicriteria Recommender Systems**
- Description of educational scenarios and resources includes rich and complex information
  → **Context-Aware Recommender Systems (CARS)**

Traditional RS: $f : Users \times Items \rightarrow Rating$
TEL RS: $f : Users \times Items\ (Learning\ Context) \rightarrow Rating$
CARS: $f : Users \times Items \times Context \rightarrow Rating$

Our RS: $f : (LAs + Context) \times Items \rightarrow Rating$

The Semantic Model

The recommender relies on a **Semantic Model**. It is composed of an ontology, identifying all relevant terms needed to describe the existing conceptual elements and their relations, and a set of inference rules to capture the existing heuristic knowledge that cannot be expressed using Description Logic formalisms designed by the iTEC partners to collect implicit knowledge about the domain (Universe of Discourse) and support recommendation tasks.



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Multicriteria algorithm

We treat the recommendation problem as a multicriteria decision problem according to the Roy's methodology.

Level 1. Definition of the Object of Decision

Relevance calculation and ranking of elements according to their utility.

Level 2. Criteria modelling (definition of families of criteria)

Three types of resources → Three distinct families of criteria:
(1) software/hardware tools, (2) events and/or (3) contributors (experts, parents and other external potential contributors to a learning activity).

$$\text{(S0) General rule} \begin{cases} g_i(a) \in [0, 10] & \\ g_i(a) = 1 & \text{if the option has the worst possible rating} \\ g_i(a) = 5 & \text{if the criterion cannot be assessed} \\ g_i(a) = 10 & \text{if the option is totally relevant} \end{cases}$$

On the basis of this general rule, we can distinguish four strategies to compute relevance according to a given criterion.

(S1) Non-weighted

$$g_i = 5 + \frac{\#vals}{\#vals\_req} \cdot 5 \qquad (1)$$

(S2) Proximity

$$g_i = 10 - \frac{x}{th} \cdot 5 \quad x \leq th \qquad (2)$$

(S3) Weighted

$$g_i = \frac{1}{n} \cdot \sum_{j=1}^{n} l_j \qquad (3)$$

(S4) Collaborative

$$g_i = \frac{1}{n} \cdot \sum_{j=1}^{n} r_j \qquad (4)$$

Level 3. Global preference model

Marginal utility function

$$f_i(g_i(a)) = \frac{1}{10} \cdot g_i(a) \qquad (5)$$

General utility function

$$R(a) = f(\mathbf{g}(\mathbf{a})) = \sum_{i=0}^{n} w_i \cdot f_i(g_i(a)) \qquad (6)$$

Values w_i are obtained from the arithmetic average ($\overline{w_{f_l}}$) of the rating assigned by iTEC Control Boards to the relevance of each criterion i. These weights satisfy $\frac{w_i}{\sum_i w_i} = 1$ and are computed as:

$$w_i = \overline{w_{f_l}} \cdot \frac{a}{\sum_{j=1}^{n} \overline{w_{f_j}}} \qquad (7)$$

Tool criteria	$\overline{w_{t_{f_l}}}$	Strat.
Functionality	8.43	(S3)
Language	6.65	(S1)
Application type	6.52	(S0)
Running environment	6.30	(S0)
Age range	6.30	(S1)
Education level	6.30	(S1)
Cost	6.26	(S0)
Rating	5.91	(S4)
Local technology	5.91	(S0)
User competence	5.70	(S0)

Contrib. criteria	$\overline{w_{c_{f_l}}}$	Strat.
Language	7.87	(S0)
Expertise	7.78	(S3)
Experience	7.17	(S0)
Comm. channels	6.87	(S0)
Trust	6.48	(S1)
Organization	5.78	(S0)
Rating	5.70	(S4)
Location	5.30	(S2)
Knows	4.96	(S0)

Event criteria	$\overline{w_{e_{f_l}}}$	Strat.
Subject	7.91	(S3)
Required tools	7.26	(S1)
Cost	6.96	(S0)
Location	6.22	(S2)
Rating	5.96	(S4)
Organization	5.96	(S4)
Age range	5	(S1)
Education level	5	(S1)

Results & Conclusions

The recommender system implementing the above described three algorithms has been tested through a testing prototype (iTEC workshops).
→ It has the **potential to lead innovation** in the classroom.

Conclusions

- The impact of some factors included may be reduced if not enough data linked to them could be identified
  → automatic enrichment of data from other sources external
- Weighting provided by the experts would require an iterative process to adjust them
  → feedback, evaluation, amount of available data
- Social tagging allowing users to add their own data is also considered.
- User rating and other paradata may be weighted based upon the confidence