A Utility-based Semantic Recommender for Technology-Enhanced Learning

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Motivation

Recommendation systems in Technology enhanced learning (TEL) help to

- ease information overload
- provide guidance and avoid disorientation

⇒ Personalization
Problem Definition

Given:

- User model (e.g., preferences, situational context)
- Item model (e.g., description of item characteristics)

Find:

- Recommend items that are assumed to be relevant
- Choose best-fit items for a particular user
- Recommend sequences of items
Personalized Recommendation: "Recommend learning objects that best fit the learner’s needs"
INTUITELE Utility-based Semantic Recommender

Didactic Recommendation: "Infer learning objects that are part of the learner’s personalized learning pathway"
Semantic Web Approach

- Describing learning resources based on Semantic Web Standards enables information sharing, integration and reuse
- Best practice vocabularies and taxonomies for LOM meta-data elements
- Support of semantic search and reasoning
  - Use ontologies to improve recommender systems
  - Knowledge-based techniques such as simple inheritance on taxonomies and logical inference
  - Instance retrieval based on didactic requirements, i.e. knowledge about how to relate learners to items
Major Challenges

- Relaxing complex conjunctive queries
- Support of soft constraints and preferences
- Ranked retrieval
- Representing learning pathways as (structured) linear sequences
Basic Approach

Combination of a

- **Knowledge-based approach** based on ontologies to describe learner, learning material and pedagogical model
  1. Choice of OWL 2 DL as recommended W3C Standard
  2. Recommend (sequences) of learning objects

- **Utility-based approach** to give a relevancy score for the best-fit Learning Object
  1. Multi-Attribute Utility Theory (MAUT)
  2. Incorporation of *Hard and Soft Constraints*

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Utility-based Semantic Recommender

Figure: Modular Ontology Framework
The Learner Model

- Captures current state of the learner ⇒ characterized by Didactic Factors
- Hard Constraints ⇒ basic learner requirements, Soft Constraints ⇒ learner preferences

User tracking, i.e.

- implicit information about the individual’s learning history
  - e.g., order of accessed learning objects, completion status, learner’s preferences for certain media and knowledge types, learning pace
- explicit information provided by the system
  - e.g., connectivity, assessment results
  - gather missing learner information through an interactive dialogue
Pedagogical Ontology

- Pedagogical knowledge based on Web Didactics (Meder, 2006)
- Learning material organized into Knowledge Domains (KDs), Concept Containers (CCs), and Knowledge Objects (KOs)
- The learning path network based on IMS Learning Design with some extensions
  - Learning pathways specified as fully connected sequences (from the start to an end node) on two hierarchical levels (i.e., CCs/KOs)
  - Property chains to link learning objects so that all those reachable from the current learner state can be inferred
  - Abstract learning pathways based on knowledge types

Figure: INTUITEL Macro- and Micro Learning Pathways
Learning Resources

- Learning objects are defined as small, self-contained, reusable units of learning and are described following the learning standards and specifications IEEE LOM.
- Metadata vocabulary based on Dublin Core and reference to domain ontologies. Metadata elements include difficulty level, EQF level, language, estimated learning time, recommended age, disabilities.
- Knowledge Types are, e.g., orientation, example, assignment, etc., and Media Types, e.g., text, video, audio, etc.
Recommendation Axioms

1. Proceed to the next/previous learning object(s) that are either partially complete or unseen.

2. Proceed to a perfect matching learning object w.r.t. the setting of Didactical Factors reflecting the current learner state.

- Needs to be configured to the specific course domain:
  - Didactical Factors: adjustment of weights required
Reasoning Infrastructure

- **In-memory Reasoners**
  Pellet, FaCT++, HermiT, TrOWL

- **Reasoning Broker Framework HERAKLES**
  Selection of the most appropriate reasoning system for a particular task.
  Different strengths and weaknesses of individual reasoners. In general, not all required features we need are supported by one single reasoner.

- **Parallelization**: Split work load to different reasoners in case of many learners.

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Ranking Strategies

Recommendation Process:

- Use reasoner to compute all result sets
- Calculate the utility of all learning objects in the result sets

- **Hard Ranking:** Didactical Factors of current learner state need to match with learning object features.
- **Soft Ranking:** Didactical Factors of current learner state need not perfectly match with learning object features.
- **Mixed Ranking:** Combination of Hard and Soft Ranking. User specifies in advance which Didactical Factors need to be fully satisfied.
Recommendation Score

1 Degree of Similarity. Parameter \( d \) is used to define how similar an item is to the one advised by the tutor on a single feature dimension.

2 Weights. Different weights can be assigned (by the tutor) to individual features, reflecting their importance with respect to all other feature constraints.

Recommendation score:

\[
\text{RecScore}(LO_i) = \sum_{k=1}^{n} w(k)d(i, k)
\]

where

- \( w(k) \) is the weight of feature \( k \).
- \( d(i, k) \) is the matching degree of the feature \( k \), represented by a floating-point value ranging from 0 to 1.
- \( n \) is the number of Didactic Factors.
Conclusion and Outlook

Major Contribution:

- Utility-based recommender approach to personalized e-Learning
- Tests on authentic courses as well as synthetic test data
  - Scalability test ⇒ Recommendation algorithm relatively fast for medium-sized curriculum courses.
  - High accuracy, albeit only for a few selected learner profiles.

Outlook:

- Increase coverage of items by linking to Open Educational Resources on the web.

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Towards a Specification of Personalized Learning Pathways

An expressive framework based on OWL 2 DL
OR: Why Directed Acyclic Graphs are not enough.
Learning Pathways in IMS Learning Design (1)

based on [IMS Learning Design, 2003]

- A **personalized learning path** is based on two inputs: the performance of the learner and the previous knowledge.
- Provides a flexible specification for describing **pedagogical models**.
- **Prerequisite**: An entry requirement for learners engaging in learning. As with learning objectives, the prerequisites can be provided at the level of the unit of learning and/or for individual learning activities.

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Further requirements for a learning path specification (2)

based on [Janssen, 2008]

- Modular composition
- Nested composition
- Directed towards an end node (i.e., Learning outcome)
- Selection of optional and mandatory items
- Specification of a fixed order in which elements of a curriculum are to be completed (Sequencing)
- Support of non-deterministic choices (Temporal coordination)
- Conditional composition
- Choice of alternative items (Substitution)

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Semantic Web Requirements for a learning path specification (3)

based on [Berners-Lee, 2009]

Data sharing & reuse based on the Linked Open Data principle

- publish resources on the web under an open license
- make them available in a structured machine-readable form
- use of non-proprietary open formats
- use of URIs to denote things
- link your data to other data (networked)

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DAGs - RDF - OWL

Learning Path

A learning path can be defined syntactically as a sequence of consecutive edges in a Directed Acyclic Graph (DAG).

- By means of **Labeled DAGs** multiple relationship between any two vertices can be expressed.
- Using **Labeled DAGs**, we can define non-deterministic choices. Feature checks can be used to guide the navigation.

- **Major shortcoming** ⇒ Do not exhibit any hierarchical structure, as linking to subgraphs cannot be achieved
RDF and Property Graphs

Resource Description Framework (RDF)

The Resource Description Framework (RDF) is a metadata model introduced by the W3C for representing information on resources in the Semantic Web.

- RDF triples can also be conceived of as a directed labeled graph ⇒ can also be used to control the navigation
- Using RDF Schema ⇒ offers offers an extra semantic layer
- Internationalized Resource Identifiers (IRIs) ⇒ enable interoperability in the Semantic Web
- Property Graphs useful to directly assert a property to a specific edge

- **Major shortcoming** ⇒ Many triples needed. Not very compact.
OWL 2 DL

Example: **OWL axioms can be used to**

- formalize the relationships between nodes (e.g. disjointness)
- automatically check the consistency of the data (e.g. existing start and end nodes, no cycles, no learning object appears more than once on the path, connectivity)
- incorporate semantic adaptivity constraints on successor/predecessor nodes
- infer pathways based on semantic attributes (e.g., Knowledge Type or Media Type Pathways) or **similar** to a reference sequence
Thanks for your attention.

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