An Intelligent Recommender System for E-learning Process Personalization
A Case Study in Maritime Education

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  • PhD in Information Systems (National Technical University of Athens)
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Outline

- Introduction
- Research Methodology
- Results
- Conclusions & Future Work
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Motivation

- The pandemic of COVID-19 caused the closing of classrooms all over the world and forced 1.5 billion students and 63 million educators to suddenly modify their face-to-face academic practices.

- **Higher education institutions** were forced to shift rapidly to distance and online learning.
  - On the one hand, this fact revealed the weaknesses of adoption and utilization of e-learning strategies and technologies as well as inequalities.
  - On the other hand, it resulted in a digital revolution of education.

- **E-learning personalization** is emerged as a major challenge, especially in today’s fast adoption of this alternative way of learning.

- Despite the large amount of research works dealing with learning profiles in physical classrooms, these models should be further investigated and validated in the virtual classrooms.
Research Objective

- The complete transformation of the physical learning process to a virtual one pose the **challenge of personalization according to different learning profiles**, a research area rather underexplored.

- The **objective** of the current paper is to develop an **intelligent recommender system** for supporting the professors in higher education understanding their students’ needs so that they **adapt the e-learning process** accordingly.

- In addition, the proposed recommender system is able to **classify new records (i.e. students) to the appropriate learning profiles**, e.g., in order to support the organization of the class groups.

- The proposed approach was applied to a **maritime educational institution**.
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The Proposed Methodology

- The proposed methodology consists of the following steps:
  
  - Data Collection and Learning Profile Model Selection
  
  - Classification for Structuring the Learning Profiles
  
  - Modelling the Relationships between Learning Profiles and E-learning Preferences
  
  - Predicting the Class Attribute of E-learning Impact
Data Collection and Learning Profile Model Selection

- The data was collected in the form of an online questionnaire addressed to students of higher educational institution.

- 80 questions in a Likert scale
  - (1: Strongly Disagree – 5: Strongly Agree)

- Each question was related to one out of the 4 learning styles as defined by the Honey and Mumford Model:
  - **Activist**: active involvement in the learning activity
  - **Reflector**: watching and thinking about what is happening
  - **Pragmatist**: learning activities where there is time to observe, reflect and think
  - **Theorist**: understanding the theory behind the action
Classification for Structuring the Learning Profiles

- The classification of students to learning profiles is not straightforward since they may have characteristics of more than one profile.

- According to the given answers, the \textit{k-means clustering} algorithm was applied in order to assign the respondents to 4 clusters (k=4) matching to the aforementioned learning profiles.
Modelling the Relationships between Learning Profiles and E-learning Preferences

- Subsequently, the proposed approach models the relationships between the learning profiles and e-learning contribution to learning factors.

- To do this, a **Bayesian Network (BN)** is applied aiming at identifying these causal and uncertain relationships.
At any time, the user of the recommender system is able to make queries in order to investigate particular relationships along with their associated Conditional Probabilities (CP).

Moreover, the model incorporates a Naïve Bayes classifier for predicting the class attribute of a learning profile as soon as new records of students’ responses are inserted.

Prediction of the class attribute can be performed even if the questionnaire is not completely answered.
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The proposed approach was applied on a dataset of 268 students of a maritime higher educational institution in Greece.

The learning process in maritime education faces additional challenges due to the structure of their programs, the tendency of undergraduate students to combine studies and work, the internationalization, specialization, and standardization.

These make maritime education an interesting case study for the validation of e-learning process personalization.

The implementation and execution of the experiments were performed using the sklearn.cluster library of Python for the k-means clustering algorithm and the BN functionalities of the pgmpy (Probabilistic Graphical Models using Python) package.
## Indicative Results

### Highest and Lowest Conditional Probabilities (CP)

<table>
<thead>
<tr>
<th>Highest CPs</th>
<th>E-learning contribution</th>
<th>Learning profile</th>
<th>CP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>F1={Neutral}, F2={Agree}, F3={Disagree}, F4={Agree}, F5={Strongly Disagree}, F6={Disagree}, F7={Neutral}, F8={Strongly Disagree}, F9={Agree}</td>
<td>Activist</td>
<td>0.386</td>
</tr>
<tr>
<td></td>
<td>F1={Disagree}, F2={Disagree}, F3={Agree}, F4={Strongly Disagree}, F5={Disagree}, F6={Strongly Disagree}, F7={Neutral}, F8={Neutral}, F9={Disagree}</td>
<td>Theorist</td>
<td>0.295</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Lowest CPs</th>
<th>E-learning contribution</th>
<th>Learning profile</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>F1={Strongly Agree}, F2={Disagree}, F3={Strongly Agree}, F4={Neutral}, F5={Disagree}, F6={Strongly Disagree}, F7={Neutral}, F8={Strongly Disagree}, F9={Agree}</td>
<td>Activist</td>
</tr>
<tr>
<td></td>
<td>F1={Agree}, F2={Strongly Disagree}, F3={Agree}, F4={Strongly Disagree}, F5={Strongly Agree}, F6={Neutral}, F7={Agree}, F8={Agree}, F9={Strongly Disagree}</td>
<td>Reflector</td>
</tr>
</tbody>
</table>

### Classification Performance

<table>
<thead>
<tr>
<th>Predicted Positive</th>
<th>Predicted Negative</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Actual Positive</strong></td>
<td>TP = 31</td>
</tr>
<tr>
<td><strong>Actual Negative</strong></td>
<td>FP = 4</td>
</tr>
</tbody>
</table>

\[
\text{Precision} = \frac{TP}{TP + FP} = \frac{31}{31 + 4} = 88.57\% \\
\text{Recall} = \frac{TP}{TP + FN} = \frac{31}{31 + 6} = 83.78\%
\]
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Conclusions and Future Work

- In this paper, we proposed an intelligent recommender system for e-learning process personalization.
  - It identifies the preferences of each learning profile in order to support the selection of the appropriate learning strategies.
  - It is based on the Honey and Mumford Model of learning profiles and utilizes k-means clustering and BNs.

- The proposed approach was applied to a dataset of 268 students in maritime education.
  - We presented indicative examples of queries.
  - We validated the model in terms of its precision and recall.

- Regarding our future work, we plan to:
  - incorporate additional learning factors with respect to the e-learning impact
  - to apply more machine learning and data analytics methods, with an emphasis on fuzzy methods
  - to expand our research to various universities in order to obtain more generalized results.
Thank you!