Module Advisor: A Hybrid Recommender System for Elective Module Exploration

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ABSTRACT

Recommender systems are omni-present in our every day lives, guiding us through the vast amount of information available. However, in the academic world, personalised recommendations are less prominent, leaving students to navigate through the typically large space of available courses and modules manually. Since it is crucial for students to make informed choices about their learning pathways, we aim to improve the way students discover elective modules by developing a hybrid recommender system prototype that is specifically designed to help students find elective modules from a diverse set of subjects. We can improve the discoverability of long-tail options and help students broaden their horizons by combining notions of similarity and diversity.

KEYWORDS

Recommender Systems; Content-based Filtering; Diversity

1 INTRODUCTION

In 2007 University College Dublin (UCD) introduced a complete restructure of all undergraduate programmes to a fully modularised curriculum which, for the first time, included two mandatory elective modules each year for every student. These elective modules provide a rich opportunity for the students to broaden their horizons, as the students are free to choose any module from any programme across the university. This provides a valuable opportunity for the students to explore their interests and strengths outside of their core area of study. However, a preliminary exploratory data analysis of historic UCD student data discovered that students' choices are often limited by discoverability challenges and overcrowded modules. Many students seem to follow the crowd or their peers' recommendations when selecting elective modules. Further the analysis revealed that the number of students choosing modules outside of their main area of study is decreasing rapidly; instead, students selected from a limited set of popular modules from their own school. Ultimately, this creates a high rate of unsuccessful allocations, as many modules have constraints on enrolment numbers and leaves the students with their second or third choice of elective module. Discoverability of modules, especially modules outside of students' main area of study and less popular modules, seems to be a big challenge that we aim to address in this research.

RecSys '18, October 2–7, 2018, Vancouver, BC, Canada

ACM ISBN 978-1-4503-5901-6/18/10.
https://doi.org/10.1145/3240323.3241613

Previous research [2, 5, 10] in the area of recommender system for academic guidance has shown the possibilities and requirements. In recent years an increase in research interest has developed and has shown the benefit of recommender systems for module exploration [1, 6]. The majority of the current research has focused on grade prediction or collaborative filtering approaches using grades as an indirect way of measuring students' preferences [3, 7]. Although we agree that the potential grade achieved in a module can be an important factor for students when selecting elective modules, in this work we focus on the module content and its relevance to students' interests.

2 SYSTEM OVERVIEW

The proposed hybrid recommender system consists of two components. Firstly, a traditional content-based (CB) recommender is used, that prioritises modules with high similarity to the students' profiles. Secondly, a hierarchical taxonomy approach is used to depict distances between modules. This approach recommends modules which are further away from those in the students' profiles.

Using the modules' descriptions from the online module catalogue we can use the Vector Space Model (VSM) [9], where each module is represented by a vector in an n-dimensional space. Each dimension corresponds to a term from the overall set of terms in the collection. Standard preprocessing of documents is performed, such as tokenisation, stop-words removal, and stemming. Term frequency-inverse document frequency [8] is used for term weighting. We calculate cosine similarities between the modules and compute the rank score of a candidate elective module, m_c, for student s_i as the mean cosine similarity between m_c and each of the modules in the student's profile, P_i, as follows: $\text{score}_{CB}(s_i, m_c) = \frac{1}{|P_i|} \sum_{m_j \in P_i} \text{sim}(m_c, m_j)$.

The second part of the hybrid recommender system is based on the hierarchical taxonomy of the academic structure of our university. The university has multiple colleges, each with a number of constituent schools. Every programme of study is associated with one of these schools and every module is associated with one or more programmes. While more sophisticated approaches are possible, here we make the general assumption that modules from the same programme are more closely related than those from different programmes. The following approach to used to calculate the rank score of a candidate elective module m_c for a given student s_i with profile P_i: $\text{score}_{TB}(s_i, m_c) = \frac{1}{|P_i|} \sum_{m_j \in P_i} \text{rel}(m_c, m_j)$, where $\text{rel}(m_c, m_j)$ is 0 if both modules belong to the same programme; 0.33 if the modules are from different programmes within the same school; 0.66 if the modules are offered by different schools in the same college; and 1 if the modules are offered in different colleges.

We combine the two approaches to allow students to better explore the wide range of elective module choices available from

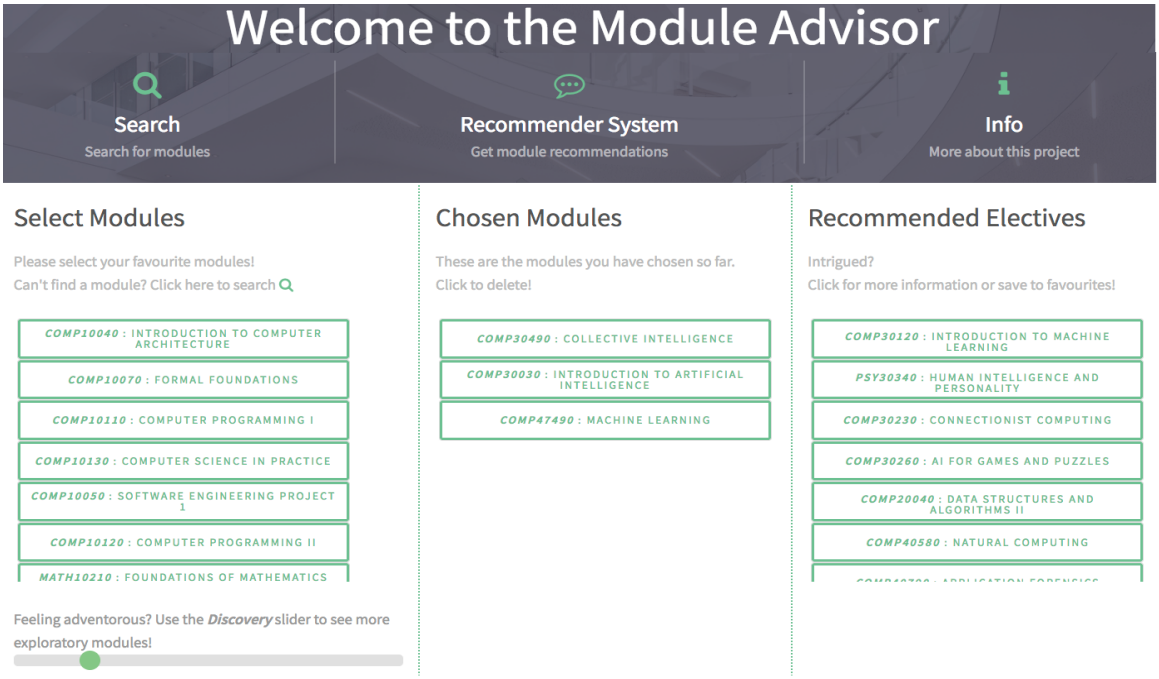

Figure 1: Screenshot of Recommender System Prototype Interface.

across the university. An overall score for a candidate elective module m_c is calculated for student s_i as follows: $\text{score}(s_i, m_c) = \alpha \ \text{score}_{CB}(s_i, m_c) + (1 - \alpha) \ \text{score}_{TB}(s_i, m_c)$, where the parameter α can be varied to influence the diversity of elective modules recommended.

3 PROTOTYPE

We have implemented the recommender system as part of a web application, see Figure 1. The application allows students to explicitly choose modules out of their module histories and receive personalised elective module recommendations. Additionally, a slider allows students to gradually increase *discovery*, which regulates the alpha value in the overall score of the recommender system and introduces more diverse modules into the recommendation list.

In the example shown in Figure 1 the student has chosen three computer science modules related to Artificial Intelligence and Machine Learning. The alpha value is set to approximately 0.3, thereby assigning a relatively low weight to the taxonomy side of the recommender system. We can see that most modules in the recommendation list are Computer Science modules closely related to the selected modules. By increasing the alpha value, the student can introduce a higher diversity into the recommendation process. With a higher alpha value, modules from diverse subjects such as Psychology, Engineering and even Forestry, which are still related to the selected modules, can be recommended.

4 CONCLUSION

Helping students to find suitable elective modules from a large number of available choices is a task clearly suited to a recommender system. This prototype represents a first step in a solution and is part of an ongoing research project to support students in making informed decisions in their academic career. In an offline evaluation [4] we have shown that the proposed hybrid recommender system can add diversity to the set of recommendations without significantly reducing relevance. This prototype is part of an extensive user study that will be conducted at our university in the near future. The results will provide insight into students' preferences and allow us to further improve the recommender system.

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