**Related work**

Identifying courses that are both of interest to the (university) students and of an appropriate level is a task that has recently gained attention in the literature. Gulzar, Leema and Deepak (2017) proposed a recommender system that uses information retrieval techniques to select courses based on student interests. Their system uses key words to search the space of possible courses but tries to improve the quality of the query by finding synonyms and generating N-grams so that the search returns a higher number of courses. Then, an Ontological Model is used to expand the search even further and retrieve courses that are related in the Ontological Model to the previously extracted courses. In this context, an Ontological Model is a knowledge model that represents relationships between concepts of a previously specified domain, such as ‘Computer Science’ (Gulzar, Leema, 2016). The system is considered to be content based because it is the contents of the courses that are matched to the concepts of the ontological model or the key words of the query. In this manner, the recommender system allows the interest of the students to be matched to the contents of the course. However, the system suffers from several drawbacks: first, the domains (e.g. Computer Science or Medicine) from which the ontological models are built must be defined a-priori (Gulzar, Leema, 2016). Second, the recommender system is dependent on a well-built database that is not always available at interested institutions.

Bydžovská (2016), developed a recommender system that takes into account a student’s past performance and interest profile to make course recommendations. Students interests are defined in a narrow sense, that is, a course is considered of interest if a student has taken the course or marked it as a favorite in the university system. Course recommendations based on interest are then made through a collaborative filtering approach: the suggested courses were the most selected courses by other students in the same field of study, or those that were taken by the n-most similar students that had already graduated. To detect risk of failure, Bydžovská (2016) predicted grades of students using classification and regression, or nearest neighbor depending on the course, binned the predicted grades into excellent, good, or bad and then issued warnings accordingly. The main innovation of the system, was that it proceeded to include social behavior and consider courses taught by a favorite teacher or taken by friends of students into the recommendations. Although the system attempts to handle both interest and appropriateness of level for a course, it suffers from a three major disadvantages: firstly, it does not provide the kind of transparent recommendation that would allow students to reflect on their course selection because the content of the course is not explicitly taken into account. Secondly, it does not give students suggestions of how to address their deficiencies. Thirdly, it does allow for a change in student interests, which is particularly important in a liberal arts context where students go through a broad exploratory phase before specializing.

Bakhshinategh, Spanakis et. al, (2017) addressed the issue of recommending courses that helps students overcome their deficiencies whilst accounting for changes over time. They view a study program as a path to obtain graduating attributes (skills, qualities, understandings) and rank the impact that each course has on promoting those graduating attributes for a student who took the course. The ranking is done through self-assessment by students after taking the course. The recommender system then uses collaborative filtering to find courses that score highest on promoting a targeted graduating attribute for a student who wishes to develop it further. Thus, if a student lacks “analytical skills”, the system identifies courses that improve these skills so that a student comes closer to the level of “analytical skills” that is required for graduation. This system can be used to find preparatory courses for other courses by shifting from graduating attributes to attributes required to succeed in a course. The main disadvantage is that the impact of each course is found through self-assessment rather than in a data driven way.

Jang, Pardos and Wei (2019) take a different approach to find preparatory courses by using Recurrent Neural Networks to develop a goal-based course recommender. A student specifies a course that they wish to take, along with the grade they desire to achieve and the system uses their personal course enrollment history and grades to find personalized preparatory courses. Although this approach finds preparatory courses in a data-driven way, it does so at the expense of transparency, which makes a student’s reflective decision making process more difficult and provides no direct insight to academic advising on how to improve the curriculum.

[INSERT LINK TO OUR WORK FITS HERE]