Goal-Driven Lifelong Learning through Personalized Search and Recommendation Services

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Abstract

The need to keep your skills up to date is becoming more and more essential in the current, permanently changing educational world. At the same time, the number of published educational content on the web is continuously increasing, while the lack of metadata and proper quality control of educational content is becoming an important issue for the search engine providers and educational recommender systems. This status quo is highly problematic for learners on the one hand when it comes to finding the most suitable educational material for their desired skills. On the other hand, this has also made the maintenance of learning pathways a frustrating job for curricula developers.

In this research, we are proposing a novel Human-AI based recommender system, which combines a learning dashboard, and an open learning content/curriculum curation dashboard into one unified system to tackle the problem of individual learning path creation and maintenance both for curricula developers and learners.

Keywords

lifelong learning, personalized learning, goal-driven learning

1. Purpose

In recent decades, we have faced a significant gap between the supply of learning content offered by educational systems, and what individuals actually need to learn to be able to carry out their daily (including job-related and social-related) activities [1, 2]. The COVID-19 pandemic intensified this challenge as due to the dramatic, and often existential situation of businesses in a number of industries forced people to re-skill themselves online in order to remain employable in post-COVID times [3]. As a consequence, lifelong learners need to monitor and update their individual skill-sets regularly to remain employable [4, 5]. For instance, skills that are important for offering online services (e.g. software development and delivery), or soft skills related to online collaboration and communication, are extremely demanded in the labor market [6] and expected to play key roles in the near future.

Subsequently, the regular updating of personal skill-sets and fast changes in the requirements

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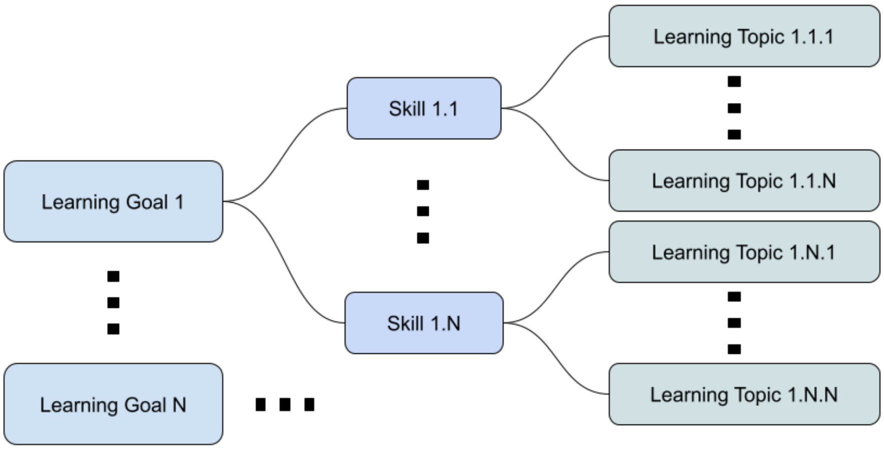

Figure 1: Three-level structure of eDoer

on the labor market side have made the process of creating and maintaining learning pathways and individual curricula inefficient and time consuming for the learning content authors [7].

As a consequence, there is a need for the development of educational systems which connect learners with curricula developers efficiently. This system should 1. support curricula developers in creating up-to-date learning pathways, and 2. provide the fittest educational recommendations to the learners toward their learning goals.

In this research we plan to help curricula developers to create different pathways by providing insights on 1. skills required by the labour market, 2. learning topics that need to be covered to achieve a skill, and 3. high-quality educational content to cover learning topics. From the learners' side, the created learning pathways are used to build a personalized learning environment for each individual learner. Therefore, the main objectives of this research are:

- Proposing a method that facilitates the utilization of information on skills for learning processes, based on timely labor market information.
- Decomposing those skills into meaningful learning objectives and their components (skills, learning topics) and offering individualized learning pathways for learners.
- Building a personalized educational content recommendation system that helps learners to achieve their goals through recommended high quality educational content.
- Utilizing artificial intelligence to help authors and experts to create a high quality knowledge base, which serves as a foundation to define a vast number of learning pathways.

2. Design

As a starting point to design our system, we created a three-level structure for the learners and content curators. *Learning goals* are on the top level, which consists of a set of *skills*. *Skills* are then divided into *learning topics*. In the end, educational contents are gathered and recommended based on *learning topics* for learners and curricula developers. This structure is shown in Figure 1.

Our approach to designing the aforementioned intelligent personalized recommender system with respect to our three-level structure consists of two modules: *Content Curation* and *Learning*.

2.1. Content Curation Module

The *Content Curation* module was built in four steps with respect to our three-level structure (i.e. *learning goals*, *skills*, and *learning topics*).

First, we created a content curation dashboard based on a three-level structure. Curators can add and maintain all three levels in the provided dashboard to create different paths for learners. These paths are dynamic and can change over time which helps the learners to be more up-to-date regarding their desired targets.

Second, we built a dynamic goal-skill matching component to monitor the changes in the skill-sets required by the labour market. The component mines the text of online job vacancies (as a proxy for learning goals), extracts the skill-related sentences and uses TFIDF to extract the skills. Afterward, the extracted skills will be sorted based on their repetition in the past six months to show their importance [8].

Third, we created a topic extractor method that decomposes a skill into learning topics. We created models by applying various text-mining algorithms (e.g. TFIDF, Latent Dirichlet Allocation, etc.) on the transcript of a large amount of educational content for a set of skills. The component uses the created models to extract the topics from the educational resources related to different skills [9].

Fourth, we developed an educational content management component to help them cover the learning topics, which 1. collects educational content from different educational content repositories, 2. classifies them according to their target subjects using our topic extractor component, and 3. validates the quality of their metadata and content using [10].

The result of this AI-aided *content curation* module is shown in Figure 2.

2.2. Learning Module

We built the *Learning* module using various components in two steps.

First, we created a learning environment which is built on top of the *learning goals*, *skills*, and *learning topics* created and maintained by the curricula developers in *content curation* module (described in Section 2.1). Learners can choose *learning goals* as their target, study the required *skills*, and receive high-quality educational content for the respective *learning topics*. This environment also allows the learners to start learning a single *skill* or even a single *learning topic*.

Second, in order to personalize the educational content provided to each learner, we created a recommender system. This recommender system creates a user profile for learners based on some key user preferences (e.g., preferences regarding different educational formats, length of content, level of details, etc.). These preferences are gathered by asking questions from the learners during their registration in the system. The recommendation system will try to match the user profile with the metadata extracted from educational contents approved by content curricula developers. Moreover, learners provide feedback (rate their satisfaction) after completing each recommended educational content during the learning process. This helps our system to capture any changes and fine tune users' profiles over time.

3. Results

Based on our developed components, we built a prototype dashboard called eDoer[1] which is available to everyone (a screenshot of a part of the learning environment is shown in Figure 3 and a screenshot of recommendations in the content curation environment is shown in Figure 4). In the curator dashboard of eDoer, curricula developers can define pathways by combining *learning goals*, *skills*, and *learning topics*. During the development and maintenance of these items, authors are aided with AI recommendations. Our system collects high quality educational content, which are relevant to the created *learning topics*. On the learning dashboard, each learner can search through all added curricula for their learning needs on different levels (*learning goal*, *skill*, or even *learning topic*). Then, they can add a list of *learning goals*, *skills*, and *topics* to their learning dashboard. In response, the system provides personalized educational content for each learner on the basis of their learning preferences. When content curators update curricula, all these updates are announced to the learners immediately so they can modify their learning pathway accordingly.

We have validated our learning dashboard in two different experiments. First, we did a preliminary validation in the *Business Analytics* course at *the University of Amsterdam*. The evaluation results showed that those students who used our prototype dashboard (24 out of 94 students used it voluntarily) achieved higher grades than those who did not use it [11]. Second, we conducted an experiment in the context of fundamental engineering skill (i.e., Basic Statistics) on 150 people in the Prolific platform[2] which is a commercial service provider for connecting researchers with participants. All the test subjects were given a pre-test and then we divided them into three groups 1. self-directed learners (not using eDoer for learning), 2. non-personalized eDoer users (using eDoer with random recommendations), and 3. personalized eDoer users (using eDoer with personalized recommendations) as shown in Table 1. After learning the selected topics for approximately 105 minutes, a post-test was taken. The difference between the post-test and pre-test scores was used as a measure of improvement in the selected area of *Basic Statistics*. The results showed that eDoer significantly improves the results of eDoer users (groups 2 and 3) compared to the self-directed users (group 1). It was also revealed that our personalized recommendations can also improve the results of learning [12].

4. Implications

This study is expected to empower lifelong learners to be able to autonomously work on their skill development. At the same time, it allows curriculum developers to define *learning goals*, *skills*, and *learning topics* faster, and keep up with emerging changes in the curriculum by getting help from artificial intelligence. Moreover, the automatic quality control component can help curriculum developers in validating the quality of their resources in various educational

[1]http://www.edoer.eu
[2]https://www.prolific.co

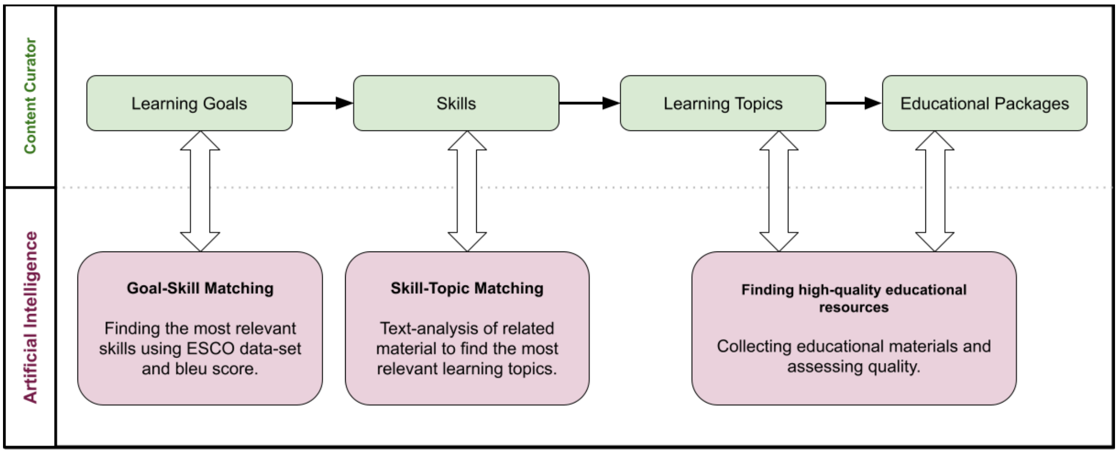

Figure 2: eDoer Human-AI interactions in the content curation module

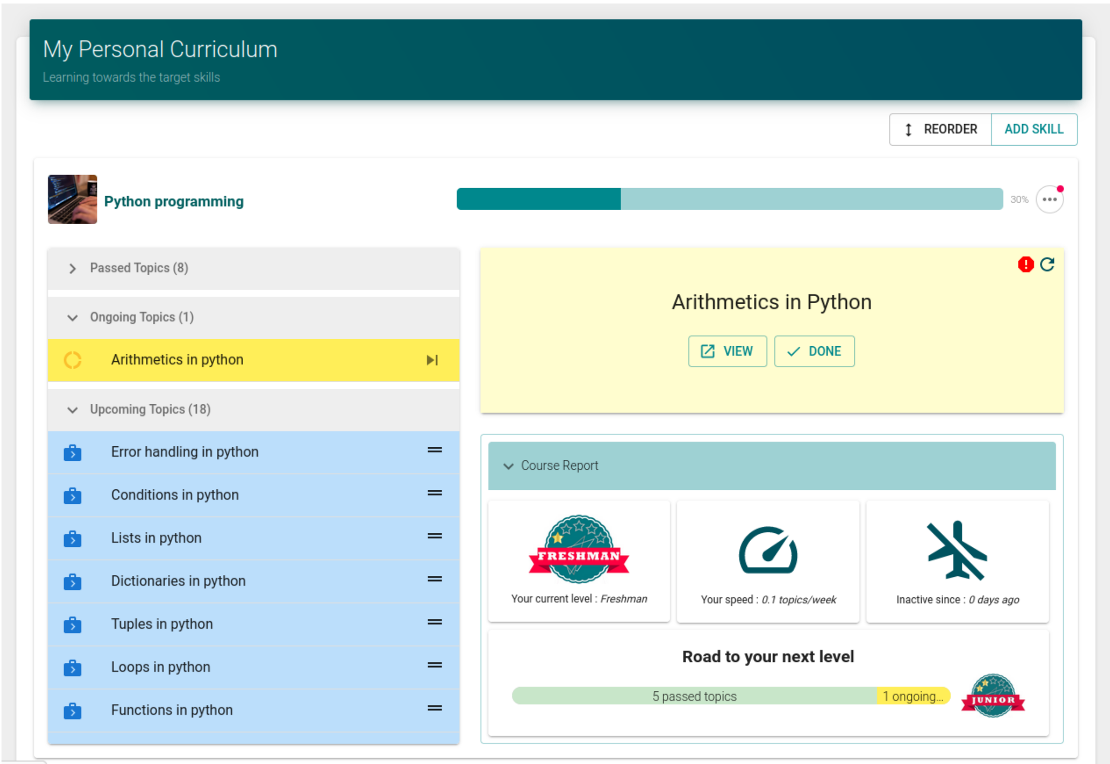

Figure 3: Screenshot of www.eDoer.eu learning environment: a learner is learning "Python Programming"

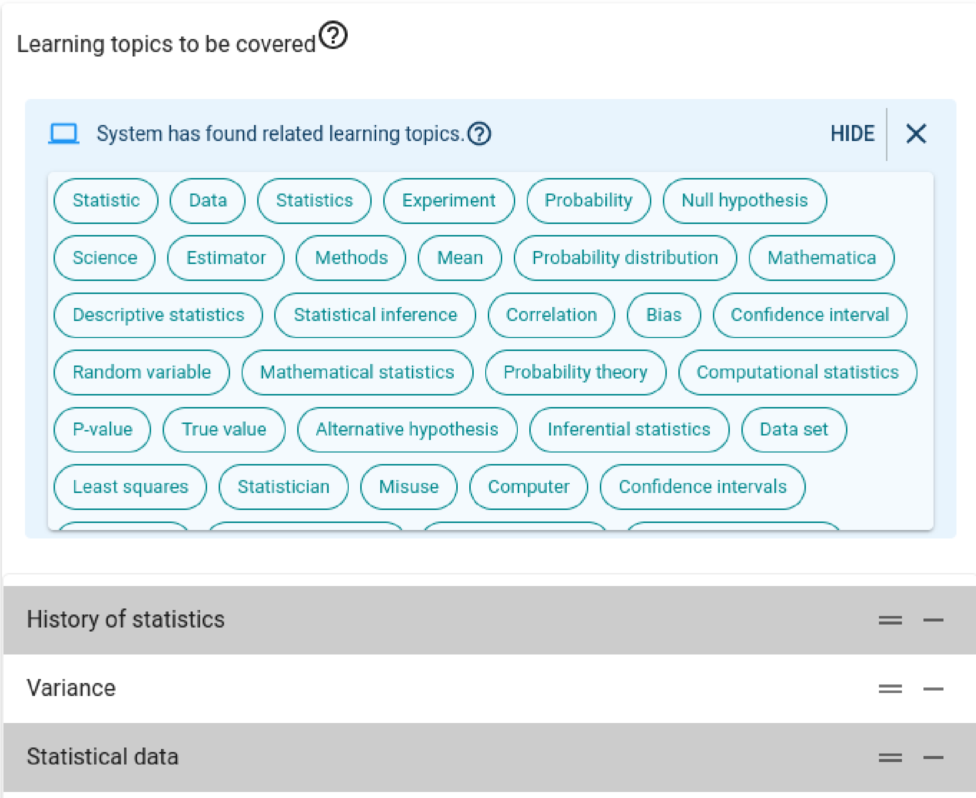

Figure 4: Screenshot of www.eDoer.eu content curation environment: a list of *learning topics* recommended to a curricula developer while trying to create the *skill* of "Statistics"

Table 1
eDoer experiment groups

Group	Task
Group 1	not to use eDoer for learning (self-directed)
Group 2	use eDoer with random recommendations
Group 3	use eDoer with personalized recommendations

content repositories. By using our method, education providers are also able to collect open educational content with high-quality metadata and subsequently, offer better recommendation and search services. These services help learners to spend less time and effort in finding related, high-quality educational content and also help authors to create and maintain the quality of their educational content more efficiently.

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- BIPER - Business Informatics Programme Reengineering, European Commission - Erasmus Plus Programme
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- WBsmart - AI-based digital continuing education space for elderly care, German Federal Ministry of Education and Research

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