NLP for Student and Teacher: Concept for an AI based Information Literacy Tutoring System

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Abstract

We present the concept of an intelligent tutoring system which combines web search for learning purposes and state-of-the-art natural language processing techniques. Our concept is described for the case of teaching information literacy, but has the potential to be applied to other courses or for independent acquisition of knowledge through web search. The concept supports both, students and teachers. Furthermore, the approach integrates issues like AI explainability, privacy of student information, assessment of the quality of retrieved information and automatic grading of student performance.

1. Motivation

Information literacy is a core skill for the digital age. In modern education and work environments it is of growing importance as knowledge work is increasingly based on large and rapidly changing knowledge sources. Search and organization of knowledge is a constant requirement. Higher education teaches information literacy sometimes in dedicated courses and often only within another course. Studies show that the level is low: E.g. students have difficulties in using operators in search terms, organize literature and tend not to know appropriate sources to find scientific literature.

The potential of *Artificial Intelligence* (AI) in higher education still needs to be explored and innovative applications need to be developed. Can computers support teaching staff in coaching information competency? – The research area "AI in Education" addresses the application and evaluation of AI methods in the context of education and training. One of the main focuses of this research is to analyze and improve teaching and learning processes. On the one hand, deep learning – learning in multi-layered ("deep") artificial neural networks – has become a central component of AI research and numerous libraries or frameworks[1] have been created that simplify the work and support the creation of own experiments. On the other hand, many educational institutions already conduct their courses, exercises, and examinations online. This means that student assessments are already available in digital, machine-readable form, offering a wide range of analysis options. Focusing on information literacy, a course typically consists of teaching material in text form and the course participants themselves practice information skills and generate text in online research and essays. However, the evaluation of free texts such as essays, references and research methodology still requires intensive manual work.

Consequently, we deal with the question which methods of *Natural Language Processing* (NLP) can support coaching of information competency and how they can be applied for the teacher, and for the student. The focus is on the combination of various deep learning approaches to automatically help students to accelerate the learning process by automatic feedback, but also to support teachers by pre-evaluating free text and suggesting corresponding scores or grades.

2. Related Work

Lazonder [1] showed that searching and talking about the search has led to positive learning effects. In a similar fashion, providing feedback and suggestions around a search activity can support the reflection on search tools' usage, on one's information needs and on the goals of the task at hand. In his keynote at ECIR 2020[2] C. Shah envisioned the next decade of research in search and recommendation where modeling

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[1] To name a few: *TensorFlow*, *Keras* , *Caffe*, *PyTorch*

[2] https://ecir2020.org/keynote-speakers/

the tasks is central to raise the quality of the results. Defined tasks around the learning of information literacy are a good example of context where recommendations can be made more relevant to the process. Intelligent Tutoring Systems (ITS) follow a long tradition of environments where AI supports learning. The most widespread didactic situation where ITS has been employed, is as exercises where a direct feedback (e.g. in form of a score or recommendation) is offered following interactions with a dedicated system. Multiple example intelligent tutoring systems exist and many follow the model of [2]. Our research aims to observe the work of the students instead of requiring exercise specific actions.

State-of-the-art research and the basis for the development of an NLP system to coach information competency include sentiment analysis [3], topic identification [4], named entity recognition [5], text summarization [6], word sense disambiguation [7] and information retrieval [8]. A major scientific challenge is the explainability of system outputs [9]. The NLP methods can be combined with knowledge graphs to include ontology-based knowledge coding in the processes [10]. This can be enhanced by including visualizations that represent both the inputs of the student and the results of the NLP analysis. Lachner [11] shows that graph representations can support the understanding of a topic. To represent ontologies or complex topics, knowledge graphs such as [12] help to identify context.

For the processing in deep learning architectures, sequences of words are encoded into vector spaces in order to perform computations in neural networks. Tools for text vectorization are Word2Vec , GloVe [13] or fastText [14]. The concept of the skip-thought vectors [15], universal sentence encoder (USE) and bidirectional encoder representations from transformers (BERT) [16] are methods also supporting sentence embeddings in the semantic vector space. [17] investigates and compares state-of-the-art deep learning techniques for *automatic short answer grading*. Their experiments demonstrate that systems based on BERT [16] performed best for English and German. On their German data set they report a Mean Average Error of 1.2 points, i.e. 31% of the student answers are correctly graded and in 40% the system deviates by 1 out of 10 points.

3. Information Literacy Courses

The term *Information Literacy* is often used synonymous with *Media Literacy*. According to the UNESCO it “constitutes a composite set of knowledge, skills, attitudes, competencies and practices that allow effectively access, analyze, critically evaluate, interpret, use, create and disseminate information and media products with the use of existing means and tools on a creative, legal and ethical basis. It is an integral part of so-called “21st century skills” or “transversal competencies”” [18]. In higher education, these information skills are highly relevant for students. Nevertheless, the information literacy of students is often measured as low [19]. Courses on basic scientific work cover several domains of information literacy. Often, there is a strong focus on searching skills, correct citing and assembling short abstracts based on scientific texts. The practice of teaching information literacy skills has not developed much towards digital formats. Some open online courses exist [20], but there is no use of AI tools yet.

An example is the ILO-MOOC (informationliteracy.eu). It allows to study in a self-paced manner. The feedback for students is show right or wrong after answering multiple choice questions. Another example is at IUBH University where bachelor students with a diverse background are trained on the basics of *scientific work*. While the focus of the assignments is in the production of written texts, it involves all aspects of information literacy. The course is made for both remote and on-site attendance and involves various communication channels, many of them happening on the web. The resulting competencies expect an independent and self-confident scientific work which may be strongly supported by an automatic evaluation.

4. Proposed System Architecture

Our concept proposes an integration within the web activities of the learner attending an assignment task which includes searching, reading, evaluating, and writing: Using JavaScript or web extensions, the text and timestamps of the search results, of the viewed publications, and of the input text can be used as features for the NLP models. Based on the assignment’s objective, the feature vectors generated from the student’s behavior and text is processed by our NLP models. The models were trained by annotated text data from previous course members (model solution, already graded works, other annotated works) to generate textual feedback.

The concept comprises several tasks for which support for students can be provided. For the sake of brevity we illustrate two of them:

A core task in scientific work and, thus, in teaching information literacy is web search. Students are often required to search for documents fulfilling certain requirements e.g. within a closed collection of documents. An AI system observes the search terms input by the student and compares the strategies to identified objectives. The system tracks the actions of the students regarding search terms, observed documents, headers and time spent. It then suggests the most appropriate steps toward reaching better results. In the example of searching in a closed collection with a pre-defined goal, suggestions for further search terms leading to relevant documents can be made.Text vectorization and a deep learning model-based classification can be used for keyword extraction [21]. As such, the student learns in the direct interaction with a search system and improves skills based on previous activities by providing automatic feedback.

Another exemplary task in teaching information literacy is related to academic writing. Students are asked to assemble a short summary and synthesis of several papers. The system supports them in analyzing the writing, recognizing the parts in a certain paper, checking whether the short summary is adequate and without plagiarism. Siamese neural networks can be used to detect similarities there [22]. The system also uses NLP to analyze the coherence of the text. Here an AI based system also gives context-dependent suggestions on how to improve the text. The suggestions provided can refer to documents, showing a title, a time when the student saw it, and a link to the document as last accessed. This is effective for the learner as the reading is kept in memory. Such support within the writing process can help students more than a theoretical unit on academic writing.

In our suggested AI based information literacy tutoring system, word sequences in search terms, retrieved documents, and reference documents are encoded into vector spaces in order to perform computations in deep learning architectures. A fine-tuning architecture, such as BERT, which has proven itself in many NLP tasks, provides the basis of our system: It is based on a pre-trained deep learning model, which — supplemented by a linear regression layer — is adapted to our specific tasks, e.g. grading short summaries or retrieved documents from the web search, and the parameters of the embeddings are tuned accordingly. A data set with labeled and graded documents and summaries from old information literacy courses serves to optimize the model for predicting scores.

To achieve a steeper learning curve and to guarantee explainability, we suggest two methods: (1) Highlighting keywords and (2) displaying the confidence score of the system's output. The keywords can be retrieved by adapting the BERT fine-tuning architecture to extract named entities as proposed in [23] and [24]. The confidence score can be retrieved by mapping the predicted scores to classes and output a vector that contains a probability for each class.

Further feedback to both teachers and learners can be given by the visualizations of individual states and configurations of the system. Given the exemplary tasks, the trial and error processes can be shown in different paths along a timeline that can be shared by the student with a teacher to allow for better feedback. Also the categorization and identification of correct steps are to be shown to the learner using clear visualizations to help understanding the decision making.

The analysis of the evolving students' work gathers data that should not necessarily be shown to fellow students or teachers: The data is made of personal trial and error processes and is to be considered as private. Other content, e.g. from chat rooms and forums, can be considered as public. It is adequate that a bot can provide answers using information that all chat members have seen (e.g. lecture scripts, assignments', posts). Similarly, submitted assignments' text data can be automatically graded based on existing information such as earlier assignments or expert texts.

5. Conclusion and Future Work

We have described the architecture of an intelligent tutoring system which combines web search and natural language processing techniques on the basis of information competency. After implementing the system and training the machine learning models, the system needs to be evaluated and optimized for students and teachers regarding usability and efficiency for which several courses exist. With the help of metrics, we reduce the error rate for training the models. Finally, we intend to speedup the system. Throughout the implementation usability tests are repeatedly performed to ensure the quality of the proposed system.

We plan to apply the architecture within several courses, adjust the tasks to be automatically measurable and annotate corpora of articles so that an automatic evaluation yields productive feedback. Using this system, we expect to answer the following questions: How to adequately capture the students' activity, select information to store and evaluate it, and how to offer support which is timely and relevant for the learning process.

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