The Dilemma of Sufficient Prediction Accuracy in Educational Recommendation Services

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***Abstract*—The study discusses the integration of technological solutions based on social media data for vocational guidance in education. It focuses on educational guidance services like «Career Guidance Robot», «Wizard», and «IOT Navigator». The analysis explores reasons for unsuccessful launches of career guidance services, emphasizing the challenge of achieving sufficient prediction accuracy and its impact on user and developer expectations. In «Wizard», for example, an accuracy of 65-67% is deemed insufficient, while 85-87% accuracy is not consistently attained across all training areas, illustrating the challenges in meeting expectations. Paradoxically, very accurate predictions may render a system ineffective, as any mistake can erode user trust, even if the system has been accurate in the past. This dilemma can be referred to as the «sufficient prediction accuracy dilemma». The effectiveness of a recommender system relies on well-defined performance targets and its future success is determined by crucial decisions regarding the inclusion of data in training, validation, and test samples. This is especially significant for recommender systems in education, where challenges like high data sparsity and non-uniformity can potentially result in the system's disruptions.**

Keywords—applicant, higher education institution, professional orientation work, navigation, IT technologies, dilemma of sufficient prediction accuracy, recommendation system

I. Introduction

In recent years, there has been a significant advancement in the development of artificial intelligence technologies, which led to the creation of numerous programs aimed at enhancing the quality of human life. The field of education is no stranger to this trend, as software products are being designed to boost the efficiency of administrative workers, teachers, and even students themselves.

At this point it should be noted that by artificial intelligence we mean the ability of intelligent systems to perform creative work and establish intricate cause-and-effect relationships, with neural networks playing the key role in their realization.

One of the priority areas of higher education, where the development of artificial intelligence technologies seems promising, is career guidance work. Choosing a profession is a crucial stage in life, and it is natural for individuals to seek ways to incorporate technology into this process to minimize the chances of potential errors.

For effective career guidance, it is important to ensure a fast access to comprehensive and objective information about an applicant's interests and expectations. Currently, social media serve as one of the main sources of such information, often acting as digital counterparts to real social interactions. Hence, it is crucial to focus on understanding the interests of social media users. This information is widely used by researchers and marketers to provide personalized recommendations and tackle various challenges in education, information security, and other areas.

II. Case of Russian-made Software Products

Before we discuss Russian-made software products that use social media data for career guidance, let's look at some examples. These include «Robot Career Guidance», «Wizard», and «IOT Navigator».

The «Robot Career Guidance» program, developed by a team from the Tomsk State University (TSU), was registered as a computer program in 2019. Using the MBTI methodology, the career guidance robot assesses the psychotype and provides recommendations accordingly, without requiring an additional questionnaire. The programming languages employed are JavaScript and PHP. The career guidance robot is accessible as a VKontakte application [1].

The «Wizard» program, developed by a team from the Ural Federal University, was registered as a computer program in 2021. Functioning as a web service, «Wizard» is designed for career guidance of university applicants. It analyzes the applicant's digital footprint on the VKontakte social network (https://vk.com/), conducts career guidance testing, suggests university programs, and provides information about potential educational programs and professions. The programming languages used include HTML, React, Next.js, Express.js, Node.js, Redux 4.1.1, and Python.

The IOT Navigator program is currently in development by teams from St. Petersburg State Technical University «LETI» and the Ural Federal University (UrFU). Unlike its competitors, «IOT Navigator» is tailored not for applicants but for university students, aiming to assist them in constructing their individual educational path. The program is expected to compare the student's profile (based on their personal page in VKontakte) with available job vacancies. It will calculate the probability of the student's employment for each vacancy, display a list of recommended activities based on the student's

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current profile and market demands, and generate a training plan to enhance employment prospects. The primary programming language intended for use is Python.

In this article, we are going to investigate how career guidance services position themselves as educational recommendation services and examines the reasons why the implementations of such services may be unsuccessful. For this purpose, we will explore the methodological framework used in the assessment of recommender services, considering both general perspectives and their application in the context of education.

Recommender systems rely on collected and analyzed data from user groups with similar characteristics. The absence of initial data creates the «cold start» problem, hindering accurate forecasting since the model lacks customer data during its construction.

Effective forecasting in recommender systems hinges on meticulously collecting and analyzing data at the outset. Decisions regarding the inclusion of data in the training, validation, and test sets have a substantial impact on the system's future success, especially in the field of education. Challenges such as high data sparsity and unevenness can potentially disrupt the functionality of the system in this context.

Checklists for evaluating data in recommender systems become crucial, both during system deployment and subsequent growth stages. It is also important to understanding the goals of a recommender system: without clarity on why recommendations are made, the system may produce chaotic and aimless suggestions.

There are four types of recommender systems:

- collaborative filtering systems,
- content-based systems,
- knowledge-based systems,
- hybrid systems.

In collaborative filtering systems, to generate recommendations, a preference matrix is created, with user ratings enhancing the interestingness and accuracy of suggestions. However, the interpretability of the system is reduced by the matrix factorization method used.

Collaborative filtering systems can be divided into two types: item-based and user-based. In item-based systems, the similarity between goods or services is established by considering the preferences of users who have provided ratings. On the other hand, user-based systems identify goods that were previously favored by another buyer with similar interests.

Content-based systems are employed by online cinemas or music services, particularly when the goal is to suggest a new product genre closely aligned with the user's previous choices. This involves creating two vectors based on user and product characteristics and determining the similarity between users and products using metrics such as cosine similarity or the Jaccard index.

Knowledge-based systems operate without considering the preferences and ratings of other users or past purchases. For instance, if you buy a sofa from a furniture store's website, the system won't suggest additional sofa options upon your return; instead, it will recommend you purchase items like an armchair, a coffee table, a lamp, and a carpet. These systems generate rules to guide product recommendations based on user interactions.

Finally, hybrid systems integrate various approaches to enhance forecast accuracy. The «Wizard» recommender system, for example, combines methods for identifying social media users' interests through profile analysis, analyzing user interests based on their social connections, and identifying interests based on content. In career guidance, the robot assesses psychotypes using the MBTI methodology to recommend professions accordingly. Meanwhile, the «IOT Navigator» system assesses the student and vacancy profiles, calculating the student's likelihood of employment.

Table 1 shows the outcomes of the «Wizard» clustering algorithm (for more detail see [2]). The presented accuracy ranges pertain to predictions across different institutes, each encompassing 3 to 38 educational programs. While the accuracy ranges vary depending on the educational programs, there is a notable degree of spread, which may be undesirable for applicants. Accuracy falling within the range of 65-67% is considered inadequate, and the accuracy level of 85-87% is not consistently realized across all training areas.

TABLE I. ASSESSMENT OF CLUSTERING ALGORITHM ACCURACY FOR WIZARD RECOMMENDER SYSTEM

UrFU institutes	List of educational programs	Accuracy, %
Graduate School of Economics and Management	38.03.05 Business informatics 38.03.04 State and municipal administration 38.03.06 Trade 38.03.02 Management	67-82
Institute of Physical Education, Sports and Youth Policy	43.03.03 Hospitality, etc.	73-76
Institute of Civil Engineering and Architecture	08.05.01 Construction of unique buildings and structures, etc.	68-74
Institute of Natural Sciences and Mathematics	03.05.01 Astronomy, etc.	67-87
Ural Power Engineering Institute	13.03.03 Power engineering, etc.	62-82
Engineering School of Information Technologies, Telecommunications and Control Systems	09.03.01 Informatics and computer technology, etc.	61-85
Institute of Chemical Engineering	19.03.01 Biotechnology, etc.	74-87
Institute of New Materials and Technologies	15.03.04 Automation of technological processes and production	63-84
Ural Institute of Humanities	46.03.03 Anthropology and ethnology	68-87
Institute of Physics and Technology	27.03.05 Innovation, 09.03.02 Information systems and technologies, 28.03.02 Nanoengineering, 12.03.01 Instrumentation, 14.03.02 Nuclear physics and technology, etc.	51-85

Table 1 illustrates the challenging operational aspect of the «Wizard» system due to its wide variation in prediction accuracy.

Firstly, the end user perceives the neural network as a «black box», creating apprehension as it lacks transparency. Users are dissatisfied because they lack understanding of why they receive specific recommendations or how they are similar to other users, seeking recognition of their uniqueness.

Secondly, the «Wizard» developers' focus on a specific applicant in issuing recommendations led to expectations of 100% accuracy on the part of applicants. Note that people's fear of machines is rarely associated with a fear of the machines themselves. Often, people are afraid not of cars, but rather of their mistakes. You can recall the barrage of angry calls to the technical support of telecom operators during temporary Internet outages. Trust in machines is undermined very strongly and instantly; unlike people, machines have no room for error in the eyes of users.

Thirdly, when considering an acceptable error rate for recommending a four-year educational program, there is an expectation that errors are never acceptable, especially for crucial decisions like planning a future profession. A good system is seen as the one that consistently provides accurate recommendations.

Fourthly, the effectiveness of a system is inversely proportional to its efficiency. Advertisers and clients might favor a very good recommender system because of its honesty in suggesting the best options, such as the best educational programs. As a result, lesser-known programs might receive fewer recommendations, leading users or administrators to question the value of including these programs in the system, as they are overshadowed by more popular choices.

Matthias Hunold, Reinhold Kesler, and Ulrich Laitenberger [3] highlight how the ranking algorithm of Booking may prioritize hotels with better external offers, potentially leading buyers to overlook more profitable options. The recommender system tends to favor products purchased more frequently, relying on past purchase probabilities to predict future sales. This bias is not unique to hotel systems; airline owners have been found to manipulate algorithms to prioritize their flights over competitors' flights, impacting user search results.

III. CONCLUSION

In conclusion, a system that consistently makes accurate predictions may not be effective for all stakeholders. Even a single mistake can erode trust, overshadowing the system’s correct answers in the past. This dilemma, which can be described as the «dilemma of sufficient accuracy», underscores the importance of maintaining user trust in a recommender system.

If developers, customers, and users treat a neural network as a black box, they face the challenge of achieving sufficient accuracy. The TSU «Robot Career Guidance» system offers a more practical approach, designed not as an individual counseling tool but as a marketing tool for selecting applicants on VK for targeted advertising invitations. The dataset relies on psychotyping rather than digital traces, ensuring that applicants perceive the communication as advertising rather than psychological testing.

The alignment of system goals with expected performance determines the effectiveness of a recommender system. Possible metrics for assessment include an increase in the number of applicants or university partners from the industry, a rise in applicants willing to enroll in programs with tuition reimbursement, an increase in university income, and an extension of user sessions on the university website. The chosen metric shapes the overall goals of the recommender system, highlighting the need for developers to align their ideas with the expectations of stakeholders and users.

Transparency from developers is crucial in making administrative decisions about a particular program's operation. Three mechanisms for ensuring transparency include active promotion, where information about the recommender system is openly accessible, passive transparency through the provision of additional documentation upon request, and transparency in joint work, involving stakeholders and the public in decision-making processes. Transparency is vital across various functional fields, encompassing process and organizational transparency, thematic transparency, transparency in decision-making, evidential transparency, and consultative transparency. Such comprehensive transparency ensures clarity in the goals of an educational recommender system.

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