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An Efficient Processing Model for Improving Technology Teaching

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ABSTRACT

The paper proposes a practical teaching platform for engineering students based on a tag based talent search algorithm, aiming to bridge the gap between theoretical education and real world engineering demands. Traditional teaching methods often neglect hands on experience, limiting students' problem solving and teamwork abilities. To address this, the authors design a system that matches students with suitable practical projects by aligning student tags (e.g., skills, interests, experience) with project tags (e.g., domain, complexity, type). The algorithm leverages techniques like TF-IDF, binary encoding, and classification models (e.g., Naive Bayes, neural networks) to enable precise matching. The study outlines steps including tag definition, feature selection, dataset construction, algorithm training, and performance evaluation using metrics like accuracy, recall, and F1 score. Experimental results suggest that increased historical data improves recommendation accuracy, though the tag based approach shows comparable though not always superior performance against other algorithms in large data scenarios. The platform enhances students' practical competencies and employability while supporting applied talent cultivation models in engineering education. However, the research acknowledges limitations, such as a small dataset and the need for broader algorithm comparisons. Future work includes scaling the dataset and exploring alternative matching algorithms to improve generalization and effectiveness. The paper contributes to the growing field of intelligent educational systems by integrating talent matching algorithms in to engineering pedagogy.

Keywords: Tag based Talent Search Algorithm, Engineering Applied Talents, Practical Teaching Platform

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1. Introduction

As society evolves and industries transform, the training of professionals in engineering disciplines is gaining more focus. Conventional teaching techniques are insufficient for fostering students' practical skills and boosting their competitiveness in the job market [1]. Thus, creating a hands on teaching platform for engineering talent, utilizing a tag based talent search algorithm, is crucial. The primary objective of nurturing applied engineering talents is to enhance students' practical skills, equipping them to tackle real world engineering challenges. Traditional classroom instruction tends to concentrate on delivering theoretical knowledge, often neglecting the design and execution of practical activities. The significance of practical teaching lies in enabling students to apply their theoretical knowledge to real engineering projects, thereby improving their abilities in problem analysis, problem solving, and teamwork. Consequently, developing a practical teaching platform is essential in advancing students' practical skills in engineering. In this context, the tag based talent search algorithm plays a critical role [2]. This algorithm serves as a talent matching approach that offers personalized evaluation and alignment of talents with job opportunities [3]. Student tags may encompass professional skills, interests, practical experience, among others, while project tags might include technological domains, types of projects, and levels of complexity. By aligning student tags with project tags, it is possible to achieve accurate pairings of students with practical projects that resonate with their attributes and requirements, thus enriching their practical experience and educational outcomes. In this research, we will concentrate on the traits and needs of engineering students to develop a practical teaching platform founded on the tag based talent search algorithm [4]. Initially, we will examine the needs and design principles of the practical teaching platform to delineate its objectives and functions [5]. Next, we will discuss the principles and applications of the tag based talent search algorithm and propose a platform architecture based on this methodology. Following that, we will assess the platform's effectiveness and viability through real world case studies. Finally, we will summarize our findings and consider future research avenues [6]. This study aims to enhance our understanding of how to train engineering students with robust practical skills by transforming traditional educational approaches, thereby increasing their market competitiveness and fostering mutually beneficial partnerships between enterprises and the scientific community.

2. Related Work

The development of practical teaching platforms has emerged as a significant area of research in education. Various practical teaching platforms for engineering fields have been created, such as engineering practice and experimental teaching platforms. While these platforms typically offer practical projects and experimental tasks, challenges still exist in effectively pairing students with projects. Hence, this research seeks to address this issue by implementing the tag based talent search algorithm to accurately match students with practical projects. The tag based talent search algorithm is a talent matching technique that has garnered considerable interest in recent years. This algorithm ensures precise alignment of talents and positions by utilising tags [7]. Relevant research mainly focuses on the definition and extraction methods of tags and the design and optimization of matching algorithms. This research will build upon these achievements and refine the tag based talent search algorithm to facilitate matching between engineering students and practical projects. The applied talent cultivation model is one of the important directions in current higher education. This model emphasizes cultivating students' practical and innovative abilities to meet the needs of society and industries. In engineering majors, implementing the applied talent cultivation model requires giving full play to the role of practical teaching. Therefore, this research will explore how to support and promote the implementation of the applied talent cultivation model for engineering majors by constructing a practical teaching platform. Talent matching algorithms are methods that match students with practical projects and have been widely used in education [8]. These algorithms are usually based on students' individual characteristics and needs and the requirements and conditions of practical projects, achieving precise matching of students with practical projects [9]. This research will draw on the application experience of talent matching algorithms in education, combine the characteristics and needs of engineering students, and design a talent matching algorithm suitable for cultivating applied talents in engineering [10]. In summary, there is still a need for in depth research on the development of a practical teaching platform for engineering talent. This research will design and construct a practical teaching platform suitable for engineering students by introducing the tag based talent search algorithm to enhance students' practical abilities and employability.

Tag based teaching platforms show promise for talent identification and expert recommendation, though evidence is limited and primarily conceptual rather than empirically validated.

The available evidence comprises four relevant studies with modest empirical validation. Baoguo Yang et al., [11] 2014 demonstrated that tag based expert recommendation outperformed topic based methods using Stack Overflow data, showing tags are "more informative and valuable" for identifying expertise than general topics. Aleksandra Klašnja-Milićević et al., [12] 2018 evaluated tag based recommendations in a programming tutoring system, finding that tensor factorization with tag clustering improved recommendation quality while reducing computational requirements.

Jun Ming Chen et al., [13] 2011 developed a tag based early alert mechanism (TEA) for monitoring student progress, though specific performance metrics weren't provided. Yuanyuan Mu et al., [14] 2018 proposed using "tag words" as knowledge nodes for navigation and learning pathways in translation learning, but this remained largely theoretical.

However, the evidence base is limited most studies lack large scale validation, participant numbers aren't specified, and effect sizes aren't quantified. The concept remains promising but requires more rigorous empirical validation.

3. Design of Tag based Talent Search Algorithm

Current research primarily centers on the definitions and extraction techniques of tags, as well as the design and refinement of matching algorithms. This study will leverage these research findings to enhance and implement a tag based talent search algorithm, thereby facilitating connections between engineering students and real world projects. The applied talent development model is a key focus in modern higher education, highlighting the importance of fostering students' practical and innovative skills to align with societal and industrial demands. In engineering disciplines, executing this applied talent development model necessitates maximizing the impact of practical teaching. Consequently, this study will investigate how to support and advance the implementation of the applied talent cultivation model for engineering students by developing a practical teaching platform. Talent matching algorithms serve as tools that pair students with practical projects and have gained considerable traction in educational settings. These algorithms typically rely on the individual traits and needs of students alongside the requirements and conditions of practical projects, enabling precise pairings between students and practical opportunities. This research will utilize the experiences derived from the application of talent matching algorithms in education, integrating the characteristics and needs of engineering students to formulate a talent matching algorithm tailored for nurturing applied talents in engineering. In conclusion, there remains a significant need for comprehensive research in to the development of a practical teaching platform that fosters the development of applied engineering talents. This research will design and create a practical teaching platform suitable for engineering students by incorporating a tag based talent search algorithm to enhance students' hands on skills and employability.

To establish a practical teaching platform for engineering applied talents utilizing a tag based talent search algorithm, it is essential to devise an efficient and precise classification algorithm that aligns the tags of students with those of practical projects. The following outlines the crucial steps in the algorithm's design: First, we must define the tags for both students and practical projects. Tags for students may encompass professional skills, interests, hands on experience, etc., while tags for practical projects may involve technological fields, types of projects, levels of difficulty, etc. The tag definitions must be specific and clear to ensure accurate matching. The precision and thoroughness of tag extraction will directly impact the efficacy of the subsequent classification algorithm. Before deploying the classification algorithm, we must carry out feature selection and tag representation for both students and practical projects. Feature selection aims to identify the most representative and distinguishing features to enhance the effectiveness of the classification algorithm. Common methods for feature selection include information gain, chi square tests, and correlation coefficients. Feature representation involves encoding the selected features in a computable manner. Typical methods for feature representation include vector representation and one hot encoding. For tag features, binary encoding is commonly employed, where each position indicates whether a specific tag is present. Ranking algorithms can assess the significance of particular information, such as a specific search term, helping us comprehend and capture specific details more effectively.

$$idf(t, D) = \log\left(\frac{N}{n_t + 1}\right) \qquad (1)$$

N represents the entire capacity of the current document collection, and *nt* refers to the capacity of texts that contain the term "*t*". Setting 1 as the numerator value can prevent certain specific features from being overlooked, thus ensuring a non zero value. TF-IDF, as a widely used search engine ranking algorithm, is characterized by its easy acceptance of the basic concept and ease of operation. It is widely applied, especially in the early stages of Internet search engines.

Before implementing the classification algorithm, we must construct a training and evaluation dataset. This dataset should include the tag information of students and practical projects, along with corresponding classification labels (whether they match or not). The dataset can be constructed by collecting data from students and practical projects or through manual annotation. The construction of the dataset should follow certain principles, such as ensuring its balance, representativeness, and scalability. Moreover, the dataset should cover various types of students and practical projects as much as possible to improve the generalization ability of the classification algorithm. Selecting an appropriate classification algorithm is one of the key steps in the design of the classification algorithm. Classification algorithms commonly include decision trees, support vector machines, naive Bayes, neural networks, etc. The selection of the suitable algorithm should consider factors such as the characteristics of the dataset, the complexity, and the algorithm's accuracy. Please ensure you have determined any page, regardless of which collection it comes from. Please ensure you have determined any page, regardless of which collection it comes from. After extension, we will select two pages with relatively strong weights, Authority and Hub, from the original root set. The starting points for A[*i*] and H[*i*] can be adjusted freely, but in most cases, their starting points should be fixed at 1. However, we still need to continue iterations to ensure that all parameters of each page can be accurately estimated. In the calculation process, the Authority value of *i* is the sum of all relevant Hub values, expressed by formula (2):

$$A[i] = \sum_{k=1}^{n} H[k] \qquad (2)$$

where n is the number of pages in the root set. After selecting the classification algorithm, we need to train the algorithm using the training dataset. The training process will adjust the parameters and weights of the algorithm based on the tag information in the dataset so that the algorithm can accurately classify students and practical projects.

$$CS_{x,\,y} = \frac{DF_{xy}}{\sqrt{DF_x\, DF_y}} \qquad (3)$$

In this sentence, "*CSx*", "*y*", "*y*", respectively represent the total number of documents containing "*x*", "*y*", "*DFx*", "*DDFy*", and "*y*". With this equation, we can obtain the correlation between two tags, "*x*" and "*y*". We need to evaluate and optimize the results of the classification algorithm. Evaluation metrics may include accuracy, recall, F1 score, etc. We can fine tune the classification algorithm based on the evaluation results to improve its accuracy and stability. Optimization methods for the algorithm may involve adjusting parameters, increasing the size of the training dataset, improving feature selection and representation methods, etc. Through continuous iteration and optimization, we ultimately achieve an efficient and accurate classification algorithm to achieve precise matching between students and practical projects. The design of the classification algorithm is one of the key steps in constructing the engineering oriented applied talent training practical teaching platform based on the tagged talent search algorithm. By defining and extracting tags for students and practical projects, selecting appropriate features and classification algorithms, constructing training datasets, and evaluating and optimizing classification results, we can achieve precise matching between students and practical projects. This will contribute to enhancing the practical ability and employability of engineering students.

4. Experimental Design and Analysis

To realize the engineering oriented applied talent training practical teaching platform based on the tagged talent search algorithm, experimental design and classification are crucial steps. The key aspects of experimental design and classification are as follows: Firstly, we need to clarify the purpose and research questions of the experiment. For example, we can study how to improve engineering students' matching and comprehensive abilities in practical projects through the tagged talent search algorithm. The research question can be how to design a classification algorithm to match the tags of students and practical projects accurately. The experimental design includes the overall architecture and flow design of the experiment. The overall architecture should include data collection, preprocessing, feature selection and representation, classification algorithm training and evaluation, etc. The flow design should specify the specific operations and use of experimental equipment for each step.

The data preparation process is shown in Figure 1. Through data transformation, complex data can be converted into more accurate measurements to achieve the goal of data analysis. This study uses neural networks and the C5.0 algorithm to achieve this goal and processes the data accordingly based on different data types. After the improvement of the algorithm, its accuracy has been significantly enhanced. In addition, in the recommendation system, the amount of historical data also significantly impacts the results. From the graph above, using a recommendation system based on bipartite graphs, it can be clearly seen that with the increase of historical data, the algorithm's accuracy also significantly improves. Compared to other algorithms, when dealing with a large amount of data, the performance of the label-based algorithm is not significantly superior to other algorithms. Before experimenting, we need to collect relevant data on students and practical projects. Student data can include their grades, practical experiences, interests, etc., while practical project data can include project task descriptions, guidelines, etc. The collected data needs to be preprocessed to improve the effectiveness of the subsequent classification algorithm. Preprocessing may consist of data cleaning, data filling, data balancing, etc. Cleaning the data can remove noise and outliers, filling the data can address missing values, and balancing the data can address the problem of imbalanced samples. Before applying the classification algorithm, we need to perform feature selection and representation on the data of students and practical projects. The purpose of feature selection is to select the most representative and distinguishing features to improve the effectiveness of the classification algorithm. Common feature selection methods include information gain, chi-square test, correlation coefficient, etc.

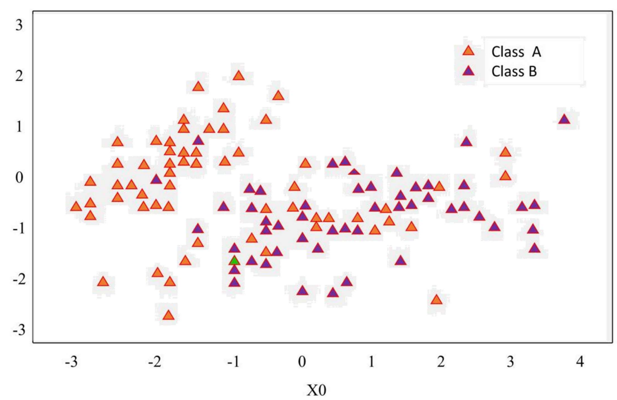

Figure 1. Naive Bayes Co-occurrence Failure Data Graph

Figure 2 shows that the page views (PV) of the tagged talent search closely aligns with the number of IPs, proving that the DCR algorithm we established is practical. Feature representation is the process of expressing selected features in a form that a computer can process. Common methods of feature representation include vector representation, one-hot encoding, etc. Binary encoding is often used for label features, where each position indicates whether a specific label is present. Selecting a suitable classification algorithm is one of the key steps in experimental design. Common classification algorithms include decision trees, support vector machines, naive Bayes, neural networks, etc. The choice of an appropriate algorithm should consider the dataset's characteristics, algorithm complexity, and accuracy, among other factors. After selecting the classification algorithm, we need to train the algorithm using the training dataset. The training process involves adjusting the algorithm's parameters and weights based on the label information in the dataset to classify students and practical projects accurately.

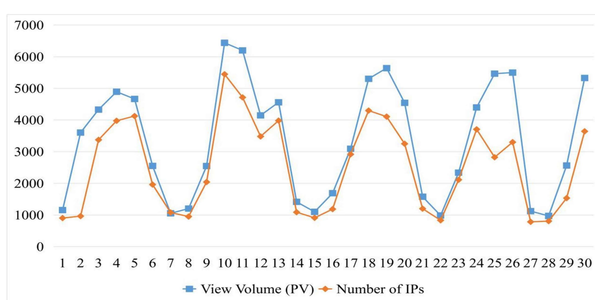

Figure 2. Tagged Talent Search Page Views (PV)

Figure 3 shows that when Map values are at 0.53 and 0.63, the accuracy decreases as the recall increases, and when the recall reaches 1, the accuracy drops to zero. Evaluation metrics can include accuracy, recall, F1 score, etc. Based on the evaluation results, we can optimize the classification algorithm to improve its accuracy and stability. Optimization methods may involve adjusting the classification algorithm's parameters, increasing the training dataset's size, improving feature selection and representation methods, etc. Through continuous iteration and optimization, we can eventually achieve an efficient and accurate classification algorithm to realize precise matching between students and practical projects. Experimental design and classification are crucial in constructing an engineering focused practical teaching platform based on the tagged talent search algorithm. By clarifying the experiment's objectives and research questions, designing an experimental plan, collecting and preprocessing data, performing feature selection and representation, choosing appropriate classification algorithms, conducting training, and evaluating and optimizing the results, we can accurately match students and practical projects. This will improve the practical skills development and employability of engineering students.

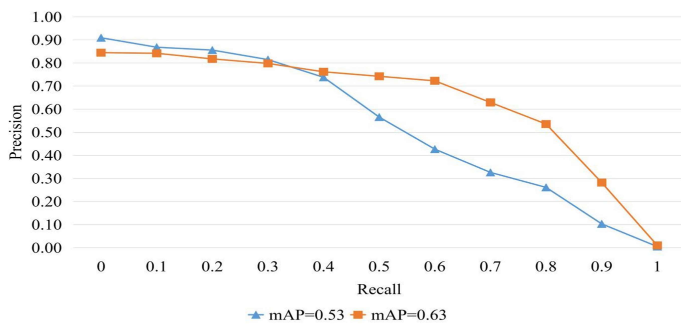

Figure 3. Changes in Accuracy and Recall at Different Map Values

5. Conclusion

This research explores the construction of an engineering focused practical teaching platform based on the tagged talent search algorithm. Through experimental design and classification, we clarified the experiment's objectives and research questions and proposed corresponding experimental plans. During the experiment, we collected relevant data of students and practical projects and preprocessed them, including data cleaning, data filling, and data balancing. Then, we performed feature selection and representation to select the most representative and distinguishing features and expressed them in a form that a computer can process. Selecting a suitable classification algorithm was a key step in the experimental design. Considering factors such as the dataset's characteristics, algorithm complexity, and accuracy, we ultimately chose a classification algorithm suitable for our experimental objectives for training. Through the training process, we adjusted the algorithm's parameters and weights to classify students and practical projects accurately. Finally, we evaluated and optimized the experimental results. Evaluation metrics included accuracy, recall, F1 score, etc. By analyzing the evaluation results, we fine tuned the classification algorithm and improved its accuracy and stability. Through the research on experimental design and classification, we successfully implemented the construction of an engineering focused practical teaching platform based on the tagged talent search algorithm. This platform can precisely match students and practical projects through tag matching, thus enhancing students' practical skills development and employability. However, this research still has some limitations. Firstly, due to time and resource constraints, we only used a limited dataset for experimentation. Future research can consider expanding the dataset to improve the classification algorithm's generalization ability. Secondly, we used specific classification algorithms in this study, and other algorithms can also be explored and compared to find more optimal solutions.

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