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Construction of a Machine Learning-Based Decision Model for Ideological and Political Education in Higher Education Institutions

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Abstract: With the rapid development of computer technology and artificial intelligence, research on machine learning-based decision-making in ideological and political education at the university level has become a crucial focus in the field of education. This research project aims to leverage machine learning methods and data analysis techniques to construct a machine learning-based analytical approach for decision-making in ideological and political education at universities, providing effective theoretical support for decision-making in this context.The project involves an in-depth investigation and analysis of the requirements for decision-making in ideological and political education at the university level. Through interviews and surveys of education decision-makers, the study aims to understand the challenges and needs they face in the decision-making process. Subsequently, a substantial amount of student learning data and relevant educational resource data will be collected, followed by data preprocessing and feature selection. Various machine learning methods and data mining techniques, such as Support Vector Machines (SVM), will then be employed for association analysis and modeling of the data.By mining student learning data, the research seeks to uncover latent information related to students' learning performance and educational needs. Based on this exploration, a machine learning-based decision support system for ideological and political education at the university level will be constructed.

Keywords: Machine Learning; Ideological and Political Education; University Student Education; Multi-trait Network; Decision Model

Introduction

At present, research on machine learning-based decision-making in ideological and political education at universities is still in its infancy. Some international universities and research institutions have begun to focus on the study of intelligent-assisted educational decision-making systems, including the analysis of student learning data and behavior, and the provision of personalized learning recommendations. However, research in the field of ideological and political education is relatively scarce. Academic attention on the ideological and political education of university students mainly centers on various new media, self-media, social media, instant messaging technologies, bringing opportunities, challenges, and relevant studies on university strategic analysis in the field of ideological and political education[1].

Ideological and political education in universities is an important means of cultivating the comprehensive qualities and correct values of college students. The application of modern computer algorithms and data analysis techniques provides a new scientific approach to educational decision-making. Through the design of a machine learning-based decision support system for ideological and political education at universities, it is possible to scientifically analyze students' learning performance and needs, provide decision support for education decision-makers, and allocate educational resources reasonably[2]. The research outcomes will provide scientific and data-driven decision support for university education decision-makers, assisting them in accurately understanding students' learning conditions and needs, and promoting the reform and improvement of university education. This study will drive the development of educational technology, promote interdisciplinary collaboration and integration, and bring new technological innovations and applications to the field of education.

1. Model establishment and solution

1.1 The establishment of numerical encoding

Processing survey data on ideological and political education in universities involves transforming data symbol sequences into corresponding numerical sequences according to specific rules, facilitating numerical analysis.

To filter out potential random background noise and analyze the characteristics of signal regions from multiple perspectives, this paper employs an entropy-based feature extraction method[3].

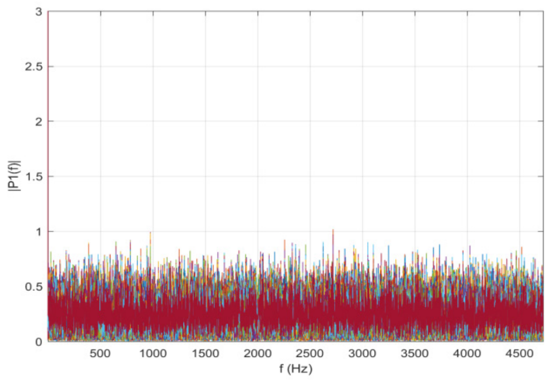

Figure 1: Data Encoding Diagram

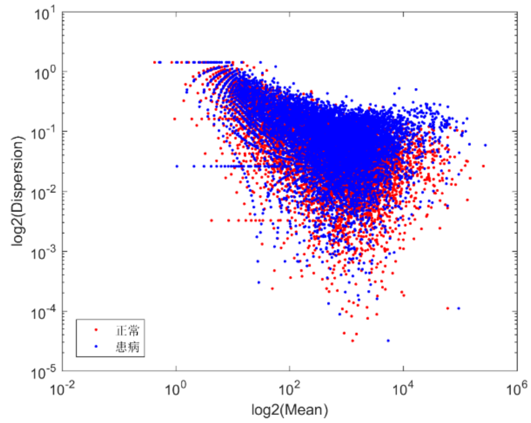

Figure 2: Distribution Chart of Sample Types After Data Processing

Utilizing an entropy-based calculation method to filter out valuable signal features, the study employs initial statistical preprocessing and selects typical sequence signal patterns for feature extraction.

1.2 The feature extraction of characteristic data points

1.2.1 Method for Constructing a Multi-Trait Network

The method employed is a random permutation approach to identify significant associations between traits. By iteratively simulating random scenarios, a distribution of the number of shared loci between traits is generated. The null hypothesis posits that the number of shared loci between traits follows a random distribution. The dataset under each trait is randomly sampled, and the number of shared loci is computed, repeated 10,000 times[4].

This study defines the proportion of the true number of shared loci equal to or greater than the simulated random shared loci as the p-value. If the p-value for shared loci between two traits is greater than or equal to 0.05, a significant association is considered. Since a significance test is conducted for each pair of traits, a correction for the false-positive rate is applied to all obtained p-values through multiple comparisons. Finally, after false-positive rate control, trait pairs with adjusted values less than 0.05 are deemed significantly associated.

1.2.2 Construction of Trait Association Network

The study explores the interrelationships between traits, and the significance of connections between traits in the network refers to a significantly higher number of shared loci between two traits than the average. This indicates similar functionality between the traits, where these shared loci establish close connections with each other. In the graph, we distinguish the ten categories of traits using different colors, and the relationships between them can be observed in the following figure.

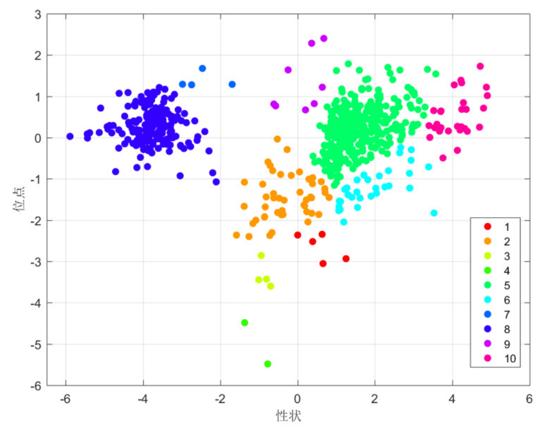

Figure 3: Schematic Diagram of the Multi-Trait Association Network

1.2.3 Module Analysis of the Association Network

Such a network of trait loci associations can reflect the similarity of loci in terms of trait functionality. Given the relatively small number of traits, a relationship is defined: if two loci both influence 10 or more common traits, they are considered to have an associative relationship.

In the end, we constructed a comprehensive network of trait associations. To better analyze the network's functionality, we utilized a Cytoscape plugin called MCODE. The MCODE algorithm was employed to analyze the network's modules from a topological perspective, identifying highly interconnected regions.

2. Site Classification Recognition using SVM

After selecting the site features, Support Vector Machine (SVM) was employed for high-dimensional mapping to achieve feature classification through the hyperplane. Subsequently, after training SVM with input samples, the SVM could classify true and false sites at given positions, i.e., site identification.Binary encoding was imported into the database, and then a sliding window size was set. True samples consisted of actual site sequences, while false samples were randomly generated sequences. These two types of samples were input into SVM, forming the support vectors for constructing the classification interface.The selected site features were obtained through an entropy-based feature extraction method, selecting features with the relatively minimum entropy value for each site[5].

Data was divided, with the selected data used as the training matrix and the mutated site data as the validation matrix. Orthogonal selection was performed using the MATLAB platform, and the parameter selection results are shown in Figure 4 and Figure 5.

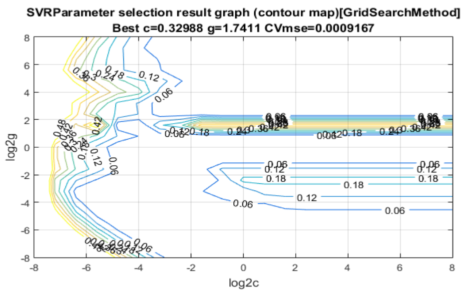

Figure 4: Contour Plot of Parameter Selection

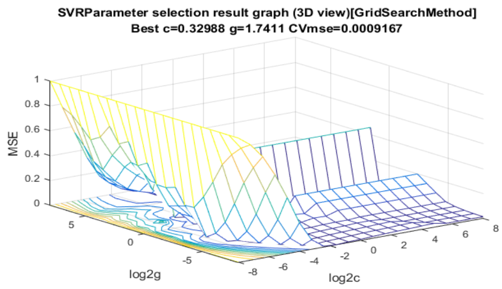

Figure 5: 3D Plot of Parameter Selection

After optimizing SVM parameters with PSO, the SVM classification plane is mapped to a two-dimensional space to form a hexagonal diagram, intuitively displaying the ranking of each participant. By using the coordinates of each cell to index athletes, detailed information about them can be obtained.

3. Conclusion

This project primarily involves the extensive collection of research outcomes on ideological and political education in universities both domestically and internationally. It leverages theoretical methods from machine learning to establish a scientific and effective decision-making system for ideological and political education at the university level. The project integrates university ideological and political education with computer algorithms and data analysis techniques, applying computer technology to the field of educational decision-making to achieve intelligent and personalized decision-making. The goal is to provide scientific decision support for university education, designing an intelligent-assisted decision support system model for ideological and political education. Through data analysis and algorithms, this system offers scientific decision support to education decision-makers, aiding them in optimizing resource allocation, enhancing educational quality and student satisfaction, promoting collaboration and communication between disciplines, and driving advancements in education research and technology.

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