A Feasibility Analysis Model for Developing Wushu Sanda Courses in Universities Based on Deep Learning

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Abstract. The current feasibility analysis of specific courses, expert analysis or single item analysis is usually used, and the results are relatively one-sided, so it is difficult to achieve a comprehensive feasibility analysis. Therefore, this paper designs the feasibility analysis model of Wushu Sanda course in universities based on deep learning. First of all, the relationship between curriculum system and training objectives is analyzed, and the relationship matrix between curriculum and objectives is established. Then according to the relationship between training objectives, the importance of the course is analyzed. After that, the training objective factors in the course are analyzed to realize the course process data. At last, use deep learning technology to analyze the marginal characteristics of data, and get the feasibility results of the course. The experiment is designed to analyze the feasibility of Wushu Sanda course in a university. The experimental results show that the model can analyze the feasibility of the course, and get the data for reference to meet the design requirements.

Keywords: Curriculum feasibility · Deep learning · Training target relationship · Marginal characteristics

1 Introduction

With the deepening of education reform, new courses have been continuously added to the original courses. Whether the added courses can achieve the training goals and the impact on other courses is one of the factors that need to be considered in the process of analyzing the feasibility of the new course [1, 2]. A strategic analysis of the Wushu Sanda courses in universities will help to discover the problems in the courses, and put forward solutions based on the existing problems, and provide certain practical guidance for the implementation and reform of the courses. Therefore, it is very important to study the feasibility of developing Wushu Sanda courses in universities.

At present, most of the domestic and foreign studies on the feasibility analysis of courses use expert evaluation methods, and most of the studies are conducted on the factors that experts need to consider, and there is a lack of research on the feasibility analysis using mathematical models. However, in related studies, there have also been methods of using analytic hierarchy process, Delphi technology and other aspects to

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analyze the single factor of the course, but it is difficult to realize the overall feasibility reference [3]. In addition, reference [4] proposed a feasibility analysis method based on the HACCP system for the management of experimental courses in universities, and explored the application of HACCP management concepts in the management of experimental courses in universities. Through combing and risk analysis of the experimental course development process, seven key control points are determined, including the submission and review of experimental projects, the condition evaluation of the experimental site, and the storage and acquisition of experimental consumables. Establish critical limits, monitoring systems, corrective measures, confirm procedures and records for critical control points in accordance with HACCP principles, and implement corresponding measures to achieve effective management and control of experimental courses. The experimental results show that this method can accurately analyze the feasibility of the management of experimental courses, but it has the problems of complicated analysis process and long analysis time. Reference [5] puts forward the feasibility analysis method of flipped classroom of clothing materials based on "rain class + SPOC". This method analyzes the feasibility of the application of flipped classroom teaching mode of "rain class + SPOC" in the teaching of clothing materials in higher vocational universities from the operability, teaching advantages and the advantages of process learning evaluation of the flipped classroom teaching mode of "rain class + SPOC". In practical application, this method also has the problem of long analysis time.

Aiming at the problems of traditional methods, this paper integrates deep learning technology into the course feasibility analysis model, and designs a feasibility analysis model for colleges and universities to develop Wushu Sanda courses based on deep learning. In the feasibility analysis of the course, it is relatively difficult because of the many factors involved and the complicated calculation. However, in the deep learning theory, the use of computer operations can achieve multi-factor analysis, the use of deep learning technology to analyze the marginal characteristics of the course data, and quickly obtain the feasibility analysis results of the course, thereby solving the traditional method of complex analysis process and analysis time longer question.

2 Feasibility Analysis Model Design of Wushu Sanda Course in Universities

2.1 Curriculum System and Operation of Training Objectives

The training goal is the soul and core of the curriculum system, which determines all other aspects of the system. Curriculum system is an organic whole of a series of courses to achieve the training objectives [6–8]. In other words, the training objectives must be supported and guaranteed by certain courses, and certain courses must be based on certain training objectives. Therefore, the optimization analysis of curriculum system must first be the interaction analysis between curriculum and objectives, so as to determine the degree of curriculum support for objectives and obtain the basis for optimizing the curriculum system. Then, the degree of realization of training objectives can be determined by calculating the number of courses supporting the objectives and the degree of support [9].

In the specific analysis, first, the cultivated target is decomposed into n sub-targets, namely $Z_1, Z_2, ..., Z_n$, in an orderly manner according to the logical relationship of self-existence. Then according to the analytic hierarchy process, according to the determined priority of the sub-objectives, the corresponding weight $w_1, w_2, ..., w_n$ is determined. At the same time, determine m alternative courses, namely $x_1, x_2, ..., x_m$, and establish a matrix table corresponding to the course department, as shown in Table 1.

Table 1. Matrix of the relationship between curriculum and objectives

P		General objective Z					
		Z_1	Z_2	…	Z_j	…	Z_n
Curriculum X	X_1	p_{11}	p_{12}	…	p_{1j}	…	p_{1n}
	X_2	p_{21}	p_{22}	…	p_{2j}	…	p_{2n}
	…	…	…	…	…	…	…
	X_i	p_{i1}	p_{i2}	…	p_{ij}	…	p_{in}
	…	…	…	…	…	…	…
	X_m	p_{m1}	p_{m2}	…	p_{mj}	…	p_{mn}

In Table 1, p_{ij} represents the degree of support for the j sub-goal in the i course. According to the value, it can have a key supporting role, an important supporting role, a general supporting role, and a small supporting role for the goal according to the value.

In order to facilitate quantitative analysis, the above four levels are assigned 1, 0.5, 0.25 and 0 respectively according to the effect of the course on the objectives, and the results are filled into the above matrix to obtain the quantitative data matrix ($m \times n$) of the relationship between the curriculum and the goal. Each row of the matrix indicates which sub goals a course supports and how much support it has. So far, the support degree of each alternative course to the sub objectives has been clarified, but how much support to the overall goal needs to be further analyzed. Therefore, the direct contribution index H of the course to the goal is introduced, which represents the direct contribution or support function of a course to the overall goal, which is obtained by weighted summation of the support degree of the course to the sub objectives:

$$H(i) = p_{ij} \times w_j \tag{1}$$

In formula (1), w_j represents the weight of sub goal j, p_{ij} represents the support degree of sub goal j in the i course, and $H(i)$ represents the direct contribution index to the overall goal in the i course. The higher the contribution index, the greater the contribution of the course to the goal, which reflects the feasibility index of curriculum development to a certain extent.

2.2 Course Importance

For the feasibility of a course, it is necessary to consider the feasibility of participating in the course arrangement and the importance of the course [10]. In this paper, consider seven representative factors, including the nature of the program, the number of weeks, the type of classroom, the number of classes, the workload of teachers and the scheduling time mode, which are represented by $C_1 \ldots\ldots C_7$. If the number of factors to be considered is set as k, then the factors to be considered are C_k, $\sum_{i=k}^{k} = 1$. Let M_k be the specific value of the k influencing factor. The obtained course priority formula is as follows:

$$PCF = \sum_{k=1}^{i} C_k \times M_k \tag{2}$$

It can be seen from formula (2) that the factors affecting the value of PCF include the size of weight and the specific value. How to determine the weight and value of each influencing factor is very important to the calculation of curriculum priority. According to the analysis of priority factors, the organization hierarchy is constructed, as shown in Fig. 1.

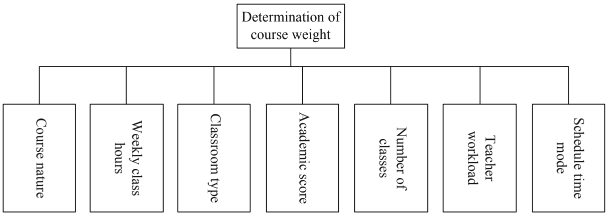

Fig. 1. Course weight hierarchy diagram

The construction of judgment matrix is the most important part of AHP, which can be divided into two steps: selecting experts and constructing judgment matrix. In the process of selecting experts, the subject structure and professional structure of experts play a decisive role in the construction of judgment matrix. In order to ensure that the construction of judgment matrix is reasonable, a total of 10 experts from computer, education and curriculum scheduling experience are selected to construct the judgment matrix. The construction of judgment matrix is actually a process of asking experts to compare all the factors shown in Fig. 1. If there is n factor in the hierarchy, $n(n-1)/2$ comparison is required, and there are 7 factors in the second layer of Fig. 1, so 21 comparisons are required.

In order to show the result of the comparison, the analytic hierarchy process puts forward a scale of relative importance. The comparison of the relative importance of two elements can be changed to get a measure. In order to illustrate the problem, there is now a factor n that has an impact on the target. Use a_{ij} to represent the relative importance ratio of B_i and B_j to the target under the influencing factors. The definition of a_{ij} can be divided into many kinds. In this article, the proportion scale is set to equal importance when the scale is 1, 3 is set to be slightly important, 5 is obviously important, 7 is really important, 9 is absolutely important, and the degree of adjacent The intermediate values including 2, 4, 6, and 8 can be represented by a matrix $A = \left(a_{ij}\right)_{n\times n}$, which is called a judgment matrix, as follows:

$$A=\begin{bmatrix} 1 & 3 & 1/3 & 7 & 1/2 & 6 & 5 \\ 1/3 & 1 & 1/5 & 6 & 1/4 & 4 & 1/2 \\ 3 & 5 & 1 & 9 & 2 & 7 & 6 \\ 1/7 & 1/6 & 1/9 & 1 & 1/8 & 1/3 & 1/4 \\ 2 & 4 & 2 & 8 & 1 & 5 & 4 \\ 1/6 & 1/4 & 1/7 & 3 & 1/5 & 1 & 1/3 \\ 1/5 & 2 & 1/6 & 4 & 1/4 & 3 & 1 \end{bmatrix} \tag{3}$$

In formula (3), A is reciprocal matrix, $a_{ii} = 1$, $a_{ij} = 1/a_{ji}, i, j = 1, 2, ..., n$. The value in the second column of the first row represents the influencing factors V1 course nature and V2 week class hours, and compares the impact of the evaluation target course scheduling effect. The result 3 represents that experts believe that the nature of the course is slightly more important than the weekly class hours, and so on to obtain the importance of the course, and arrange courses according to the importance of the course.

2.3 Curriculum Factor Analysis

p observable random vector $X = \left(x_1, x_2, ..., x_p\right)'$ is set up, which is decomposed into k dimensional ($k < p$) common factor and a special factor of p dimension, and it is written as:

$$X_{p\times 1} = Af_{k\times 1} + \varepsilon_{p\times 1} \tag{4}$$

In formula (4), $X = \left(x_1, x_2, ..., x_p\right)'$ represents the observable random vector in the course, $f = (f_1, f_2, ..., f_k)$ represents the common factor vector, $\varepsilon = \left(\varepsilon_1, \varepsilon_2, ..., \varepsilon_p\right)'$ represents the special factor vector, and $A = \left(a_{ij}\right)_{p\times k}$ represents the factor loading matrix. Given an observation data matrix X of p dimensional related variables $x_1, x_2, ..., x_p$, the purpose of factor analysis is to use a few common factors to describe the covariance structure among p related variables.

In order to establish the structure of factor analysis, it is necessary to estimate the factor load matrix $A = \left(a_{ij}\right)_{p\times k}$ and the special variance matrix $D = diag\left(\sigma_1^2, \sigma_2^2, ..., \sigma_p^2\right)$. There are many methods for parameter estimation, among which the most common method is the principal component method. Using the principal component method, let the eigenvalues of the covariance matrix of sample X be marked as: $\lambda_1 \geq \lambda_2 \geq ......\lambda_p \geq 0$, and the corresponding orthogonal unit eigenvector is: $\gamma_1, \gamma_2, ..., \gamma_p$. here, the smaller number of factors k is selected, and the cumulative contribution rate $\sum_{i=1}^{k} \lambda_i / \sum_{i=1}^{p} \lambda_i$ reaches a higher percentage.

Based on this, the factor analysis method can be used to analyze the variables of the course, and the situation of the course can be digitized.

2.4 Analysis of Marginal Characteristics of Deep Learning

In this paper, the LDA Algorithm in deep learning is used to analyze the above data. In this paper, the LDA Algorithm in deep learning is used to make each type of data obey the prior assumption of Gaussian distribution, but the actual data does not always meet this characteristic, and thus can not well describe the distinction between classes as shown in Fig. 2.

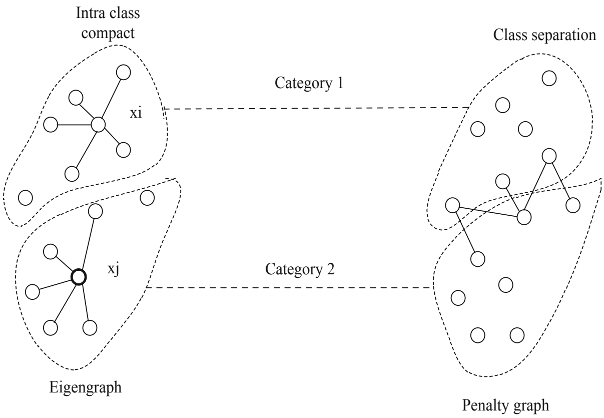

Fig. 2. Eigengraph and penalty graph of marginal embedding graph

In Fig. 2, the eigengraph describes the proximity relationship between points of the same kind. Each sample is connected with $k1$ nearest neighbor in the same kind of sample. The penalty graph describes the proximity of boundary points between classes, and different class point pairs are connected with each other. In class compactness can be described by eigengraph:

$$\tilde{s}_c = \sum_{i \in N_{k_1}^+(j) \ or \ j \in N_{k_1}^+(i)}^{n} \left\| \omega^T x_i - \omega^T x_j \right\|^2 = 2\omega^T X \left(D^c - W^c\right) X^T \omega \tag{5}$$

In formula (5), $W^c = [0{,}1]$, $N_{k_1}^+(j)$ represents the k_1 sample index sets that will be nearest neighbors in the class of sample x_j. Where ω represents the weight vector under the feature transformation.. The separation between classes can be described by (6). The concept of deep learning comes from the research of artificial neural network, and the multi-layer perceptron with multiple hidden layers is a deep structure model. Deep learning structure combines low-level features to form a more abstract high-level representation to discover the distributed feature representation of data. In the use of deep learning operation, need to consider the automatic decoder, including the parameter $\omega = [\omega_{eno}, \omega_{deo}]$, where ω_{eno} represents the encoding parameter, ω_{deo} represents the decoding parameter, and the encoding part realizes the mapping $\phi(\cdot|\omega_{eno})$ from the sample space to the feature space. The optimal parameters need to satisfy the objective cost function under the minimization formula:

$$
\begin{aligned}
\omega_{eno}^{*} &= \arg\min_{\omega} JMF \\
&= \arg\min_{\omega_{eno}} \frac{\phi_{\omega_{eno}}^{T}(X)(D^{c}-W^{c})\phi_{\omega_{eno}}(X)}{\phi_{\omega_{eno}}^{T}(X)(D^{\rho}-W^{\rho})\phi_{\omega_{eno}}(X)}
\end{aligned}
\tag{6}
$$

In formula (6), $\phi_{\omega_{eno}}(\cdot)$ represents the mapping from the sample space to the feature space. Since deep learning models have flexible function representation capabilities, they often result in overfitting training, and the generalization performance of the algorithm will be poor. To this end, it is necessary to further adopt regularization methods in the objective function. The method to obtain the internal structure distribution of the data is to minimize the reconstruction error, and the decoding part of the automatic encoding network naturally forms the reconstruction function $\vartheta(\cdot|\omega_{dec})$. The regularization defined by the unsupervised data is defined as follows:

$$
R = \frac{1}{n}\sum_{i=1}^{n}\left\| x_i - \vartheta\left(\phi_{w_{deo}}(x_i|\omega_{enc})\right)\right\|_2^2 \tag{7}
$$

In formula (7), $\| \|_2$ is the 2-norm of the vector. At the same time, it needs to be regularized. This article uses the attenuation of network weight and bias to regularize:

$$
Dec = \|\omega_{eno}\|_2^2 \tag{8}
$$

In this case, the target is transformed into the following formula:

$$
E = JMF + \alpha R + \beta Dec \tag{9}
$$

In formula (9), both α and β are regularization coefficients, which are used for feature extraction to obtain the optimal network weights

$$
W^{*} = \arg\min_{\omega} E = \arg\min_{\omega} JMF + \alpha R + \beta Dec \tag{10}
$$

After obtaining the optimized network weights, higher accuracy can be obtained in the calculation, so as to obtain the feasibility analysis results.

3 Experimental Demonstration Analysis

In order to verify the analysis ability of the feasibility analysis model of Wushu Sanda course in universities based on deep learning, the following experiments are designed to analyze the feasibility of Wushu Sanda course in a university.

3.1 Experimental Computing Equipment

Due to the large amount of data when using the model for analysis, the PC is used for relevant calculation in this paper. The configuration of PC host participating in the experimental calculation is shown in Table 2.

Table 2. Experimental PC configuration table

Equipment name	Usage amount	Device model	Device parameters
Motherboard	1	B360M MORTAR	CPU interface LGA1151, display interface DVI + HDMI + DP
CPU	1	I5-10600K	CUP main frequency 4.7GHz
Graphics card	1	RX560 4GB D5 Warrior	Graphics card memory 4GB, air cooling
RAM	2	3200 vest	Single memory capacity 8GB, memory frequency 3200 MHz
Hard disk	1	WD 1TB	Hard drive capacity 1TB, Hard disk revolutions 7200 revolutions

3.2 Experimental Calculation Process

First of all, it is decomposed according to the training objectives that the target course needs to achieve, decomposed into five sub-goals: Z_1, Z_2, Z_3, Z_4, and Z_5. At the same time, the target weight value is determined according to the above formula (1). In the experiment of this article, the determined value of the target weight is: $w_1 = 0.4$, $w_2 = 0.8$, $w_3 = 0.6$, $w_4 = 0.2$, $w_5 = 0.1$. At the same time, the candidate courses are determined. In this experiment, according to the course structure of the university, the candidate courses are $X_1, X_2, X_3, X_4, X_5, X_6$. Establish the target relationship matrix under the course, assign values to it, and get the data in Table 3.

Table 3. The target relationship matrix of the experimental course

P		Main target Z				
		Z_1	Z_2	Z_3	Z_4	Z_5
CourseX	X_1	1	0.4	0	0	0.24
	X_2	0.22	0.25	0	0.21	1
	X_3	0	0.24	0	0.5	0.24
	X_4	0.25	0.24	0.5	0	0
	X_5	1	0	0.15	1	0.25
	X_6	0.24	0.25	0	0	0.15

Use MATLAB software to program the acquired data to obtain analysis data that can be used by the LDA algorithm, and obtain the factor load table under the maximum variance rotation, as shown in Table 4.

Table 4. Maximum variance rotation factor loading table

Evaluation index	Factor1	Factor2	Factor3	Factor4	Factor5
X_1	0.07181	−0.1845	0.77216	0.14183	-0.1874
X_2	−0.05562	−0.01849	0.12741	0.22312	0.18274
X_3	0.31513	0.24521	−0.3181	0.22647	0.31826
X_4	−0.1962	−0.7415	−0.3015	0.22174	0.18612
X_5	0.45371	0.35826	−0.17651	0.18431	0.22185
X_6	−0.07132	0.22743	0.51241	0.71542	−0.1748

After obtaining the maximum variance of the rotation factor load, it is subjected to 3000 iterations of experiments. In the experiment, after 8 iterations of the LDA algorithm, the value of the log-likelihood function will reach stability, as can be seen from Fig. 3. Among them, the convergence speed is faster.

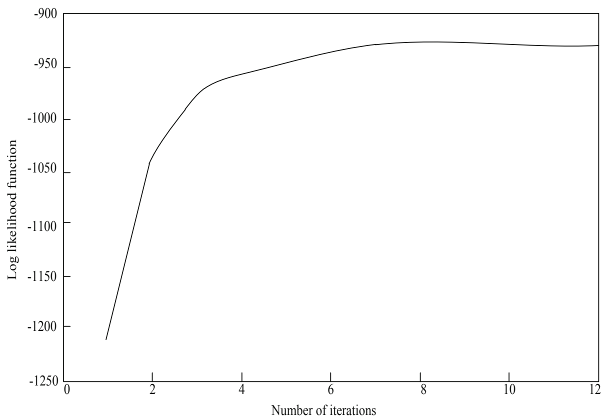

Fig. 3. Change of logarithm likelihood value of LDA Algorithm in the process of iteration

Through factor analysis of the original data, the potential variables are obtained, and the common factor comparison in Table 3 is basically consistent. The H value and T value of $H = 0.37$ and $T = 0.1746$ obtained by the model are smaller, which proves that the martial arts Sanda course Applied in the experiment has less direct contribution to the overall goal and less support for other courses. However, the numerical value also shows that the course is feasible. The course is suitable for elective courses, but not suitable for normal compulsory courses. According to the obtained H and T, complete the feasibility analysis of the course.

In order to verify the application effect of this method in the feasibility analysis of Wushu Sanda course in universities, taking the feasibility analysis time as the experimental index, the methods of reference [4], reference [5] and this method are compared, and the comparison results are shown in Fig. 4.

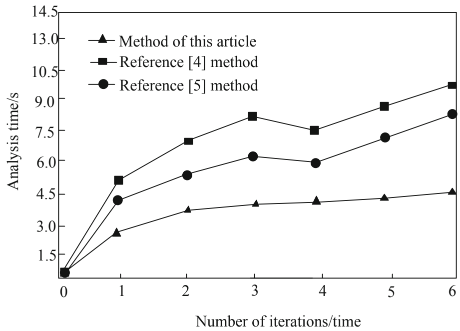

Fig. 4. Comparison of feasibility analysis time of different methods

Analysis of Fig. 4 shows that the time of feasibility analysis of Wushu Sanda course in universities is always less than 4.5 s, which is significantly lower than the traditional method, indicating that this method can realize the feasibility analysis of Wushu Sanda course in universities in a short time, and the analysis efficiency is higher.

4 Conclusion

In this paper, the deep learning technology is used to extract the influencing factors in the course, so as to realize the design of the course feasibility analysis model. The experimental results show that the analysis time of the method in this paper is shorter, which shows that the method is more efficient and effectively solves the problem of longer analysis time of traditional methods. However, the model can only give the relevant reference data and the feasibility of the course, and can not specifically allocate the curriculum itself. In the future research, according to the relevant parameters of the curriculum feasibility, the neural network technology can be used to help the calculation of curriculum allocation.

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