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# Exploration and Practice of Courses under Gaussian Mixture Model Mode

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**ABSTRACT**

*Education in universities often takes on the responsibility of moral education, which is crucial for college students' ideals, beliefs, spiritual pursuits, and political literacy. This paper analyzes the learning motivation of different student groups based on the Gaussian Mixture Model (GMM). It compares the participation characteristics of different learning motivation clusters, the differences in the performance of courses among students with different learning motivations, and the potential connections between learning motivation and learners' educational levels. In conclusion, applying the Gaussian Mixture Model in courses can help teachers better understand students' learning situations and needs, grasp the characteristics and patterns of the curriculum, assess teaching effects and issues, and thereby improve the quality and learning outcomes.*

**Keywords**: Gaussian Mixture Model, Learning Courses, Course Performance, Assessment and Evaluation

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# 1. Introduction

With the development and progress of the times, courses have become increasingly important in higher education. These courses impart knowledge and carry the significant mission of cultivating students' ethics, moral literacy, and social responsibility [1]. However, traditional ideological and political teaching models often lack targeting and effectiveness, failing to meet contemporary college students' needs and expectations. Therefore, exploring new teaching modes for courses to improve their teaching quality and effectiveness has become an urgent issue in higher education.

The Gaussian Mixture Model (GMM) is a machine-learning method based on probability statistics for modelling and analyzing complex data [2]. It assumes that data is generated by a mixture distribution composed of multiple Gaussian distributions. By estimating and modeling the parameters of each Gaussian distribution, GMM can achieve data classification and understanding. GMM can be applied to model and analyze continuous, discrete, and mixed data. Regardingconstant data, GMM can be used for modeling and analyzing speech signals, images, time series, and more. GMM can be used to classify text and images and understand discrete data. As for mixed data, GMM can be used for modelling and analyzing videos, audio, etc. [3]. GMM is an unsupervised learning method, meaning it does not require data labeling or classification; it only needs data modeling and analysis [4]. Therefore, GMM can be applied in various fields, such as speech recognition, image recognition, natural language processing, bioinformatics, and more.

In ideological and political courses, GMM can be used to model and analyze students' learning situations, course content, and formsand evaluate and analyze teaching effects [5]. By introducing GMM, we can better understand students' learning situations and needs, grasp the characteristics and patterns of the curriculum, and assess teaching effects and issues, enhancing teaching quality and learning outcomes.

This paper will explore and practice ideological and political courses under the Gaussian Mixture Model teaching mode. By introducing GMM, we can better understand students' learning situations and needs, grasp the characteristics and patterns of the curriculum, and assess teaching effects and issues, enhancing teaching quality and learning outcomes.

# 2. Related Work

By introducing the Gaussian Mixture Model (GMM), we can better understand students' learning situations and needs, grasp the characteristics and patterns of the curriculum, and understand the teaching effects and issues, thereby improving teaching quality and learning outcomes. Applying GMM in ideological and political courses has broad prospects and potential. As a result, previous researchers have conducted a significant amount of research in related fields.

Previously, scholars studied the application of clustering algorithms based on the Gaussian Mixture Model to evaluate students' performance in large-scale online classrooms. They used historical learning data, including grades, attendance rates, and completion of assignments, to conduct clustering analysis with GMM to understand students' learning situations and needs. The research aimed to provide teachers with an effective evaluation method to understand students' learning status better and develop personalized teaching strategies [6]. Other researchers proposed an online learning student performance prediction method based on the Gaussian Mixture

Model. They utilized students' learning history data, including grades, attendance rates, and participation, to train and estimate parameters with GMM. By predicting students' learning outcomes, teachers could gain better insights into students' learning progress and adjust teaching strategies timely, enhancing students' learning effectiveness [7]. Subsequently, researchers explored pattern recognition of college students' learning behavior in an online learning environment. They applied GMM to analyze students' behavior data on learning platforms to identify their behavior patterns and learning preferences. This identification method helped teachers better understand students' learning needs and habits, enabling them to adjust teaching strategies and improve teaching effectiveness [8].

Scholars also proposed a student feature selection method based on the Gaussian Mixture Model to evaluate students' learning performance in distance education. They used GMM to analyze and cluster students' learning data, selecting the most relevant features related to learning performance for evaluation. This method assisted teachers in more accurately assessing students' learning achievements and progress, leading to more effective distance education strategies [9]. Based on the success of previous research, scholars began studying how to use the Gaussian Mixture Model to predict students' performance in political education courses. The authors collected students' historical learning data, including exam scores, participation, and completion of assignments, and employed GMM for clustering analysis. By predicting students' learning outcomes, teachers could effectively adjust teaching strategies, provide personalized teaching guidance, and enhance students' grasp of political knowledge and practical application abilities [10].

In conclusion, these studies have explored the application of the Gaussian Mixture Model to analyze and solve issues related to ideological and political courses. They focused on learning performance assessment, personalized teaching, behavior recognition in online learning environments, and feature selection in distance education. These research endeavors aim to provide teachers with more effective methods to understand students' learning needs, develop personalized teaching strategies, and improve teaching effectiveness.

# 3. Gaussian Mixture Model Construction

## 3.1 Gaussian Mixture Algorithm

The Gaussian Mixture Model (GMM) comprises multiple Gaussian distributions, and the basic GMM uses linear superposition. It assumes that the data set consists of multiple latent clusters following Gaussian distributions, and the final stacking result is a presenting distribution. Although a general data set may contain different types of distributions, considering that the model is represented by a mixture of multidimensional Gaussian probability models, it can still fit any probability distribution. Assuming the random variable $X$ is a mixture of $M$ Gaussian distributions, the Gaussian Mixture Model can be represented as formula 1.

$$P(x|\ \theta) = \sum_{m=1}^{M} \alpha_m \phi\left(x|\ \theta_m\right) \qquad (1)$$

While it is generally impossible to know the components occupied by each Gaussian distribution in a mixture model, considering that the linear superposition of Gaussian distributions forms the Gaussian Mixture Model, the sum of the m weights of its constituent members is defined as 1. Given that the Gaussian model can be determined by the probability density function and parameter set è, the parameter calculation of the proposed mixture model utilizes the maximization of the log-likelihood function of the model. It seeks the optimal sample parameters that make the clustering as close as possible to the actual distribution of the samples, thus obtaining better performance in clustering results. Formula 2 represents a likelihood estimation function used to calculate key parameters of the sample data set.

$$L(\theta) = L\left(X_1, X_2, \cdots X_m; \theta\right) = \prod_{i=1}^{m} P\left(X_i, \theta\right) \qquad (2)$$

## 3.2 Expectation-Maximization Algorithm

The Expectation-Maximization (EM) algorithm was first proposed by Dempster et al. The EM algorithm is widely used in many machine learning algorithms, such as parameter estimation in K-means, Support Vector Machines (SVM), GMM, Hidden Markov Models (HMM), and Latent Dirichlet Allocation (LDA). The EM algorithm involves iteratively solving certain target parameters using a maximum likelihood estimation strategy across all data sets, including hidden variables. The iteration of the EM algorithm primarily consists of two steps: the expectation step and the maximization step. In the expectation step of the Expectation-Maximization algorithm, the model's expectation is calculated based on the model's hidden states, computing the Gaussian distribution of the guessed hidden data. Then, the model parameters are fixed, and using maximum likelihood estimation, the complete data including observed and hidden data are sequentially computed. This process finally yields the parameters of the Gaussian Mixture Model.

By analogy, the algorithm performs the M step. Then, through iterative E and M steps, i.e., adjusting the model based on parameters (E step), and then adjusting the parameters based on the model (M step), the E step and M step are alternately executed until the parameters of the Gaussian Mixture Model do not undergo substantial changes. Simultaneously, the algorithm achieves convergence, obtaining the optimal expected values for the Gaussian Mixture Model, covariance matrix, and weights of each Gaussian distribution. The expectation value of the log-likelihood function of the mixture model can be described using the initial values of the selected model parameters, as shown in Formula 3.

$$E_Q\left[\log p(\theta| Y, Q)| \theta^{(i)}, Y\right] = \int \log[p(\theta| Y, Q)]p\left(Q| \theta^{(i)}, Y\right) dQ \qquad (3)$$

## 3.3 Deep Feature Learning

Autoencoder networks are a type of neural network structure under unsupervised learning, usually consisting of three layers. The ideal goal of an autoencoder network is to reproduce the original input data. Like the Seq2Seq model in natural language processing, an autoencoder network typically consists of two parts: an encoder and a decoder. The goal of the encoding network is to transform relatively high-dimensional original input data into an encoded vector in a low-dimensional space. In contrast, the decoder network does the opposite, i.e., it reconstructs the low-dimensional vector back to the data representation in the high-dimensional space.

Next, the deep learning network model feeds the original input data into a neural network with multiple hidden layers, as shown in Figure 1. After performing non-linear operations in multiple intermediate hidden layers, the final output of the hidden layers is the same as the data input through the deep network model. The deeper it learns, the deeper the features are abstracted. However, some datasets do not have initial labels. Deep feature learning is divided into three categories based on whether the initial labels are involved in the entire network training process: supervised feature learning, semi-supervised feature learning, and unsupervised feature learning. Among them, supervised feature learning can be referred to as classification. Semi-supervised feature learning falls between supervised and unsupervised feature learning, referring to the training data containing labeled and unlabeled data.

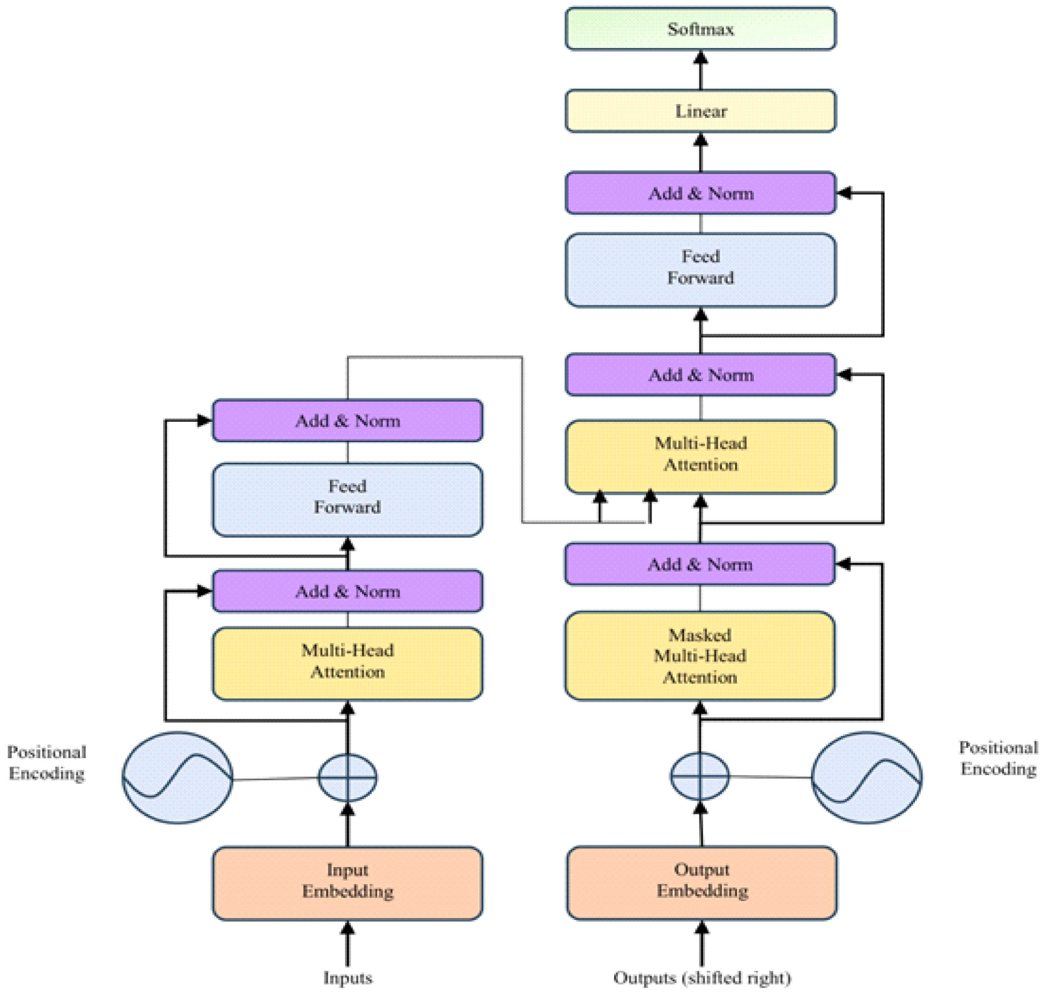


Figure 1. Flow Chart of Deep Feature Learning

# 4. Experimental Design and Analysis

## 4.1 Experimental Design

The dataset used in this study was collected and planned by researchers from the Open University, and the relevant content and materials of the courses were provided through a Virtual Learning Environment (VLE). Here, we extracted data from this platform to study two different political education courses, Course A and Course B. Student raw clickstream data collected from the Open University Learning Analytics Dataset (OULAD) was used as the analysis features. Due to some redundant features in the original feature set, we removed these features, filled in missing values, and sequentially analyzed certain features. Then, the existing features were summed and averaged to categorize the available learning into four classes: demographics, interaction behavior, registration information, and assessment information. Regarding data selection, we selected two representative courses from the Open University in 2018 and 2019. These selected courses provided course videos for over 300 students, including many students who did not pass the final grades. We chose Course A and Course B from all the courses that met these criteria, with 846 students participating in the selected courses. Finally, the data was anonymized according to the ethical and privacy requirements of the Open University.

This paper used Course A and Course B to study the relationship between motivation, student engagement, and final performance. After data preprocessing, 744 students registered for these two courses, 363 for Course A and 381 for Course B. We used the interaction data before the first assignment submission to determine the students' motivation levels based on interaction data and demographic information in the Virtual Learning Environment.

Since the analyzed learning features do not belong to the previously defined categories, this study used internal evaluation metrics to analyze the performance of the Gaussian Mixture Model. To determine the optimal number of mixtures for the final results, this section used error variance and silhouette coefficient as validation measures for the credibility and effectiveness of the results, where the Sum of Squared Errors (SSE) was used as the performance metric. The smaller the value, the higher the convergence of each mixture class. However, the value of SSE is not smaller as it approaches zero, as considering all sample points as one extreme case would result in SSE being equal to 0, which clearly cannot achieve the final classification effect. Therefore, it is necessary to find a balance between the number of mixtures and the variance of SSE. The elbow method solves this balance problem. Assuming an initial value of K, defined as the maximum possible number of mixtures, the number of mixtures is incremented from 1. The data has an underlying pattern, i.e., there is a true optimal number of mixtures, and as the number of mixtures set by the model continues to approach this value, the SSE will decrease rapidly.

## 4.2 Experimental Results Analysis

The results indicate that if students do not submit their first assignment, the probability of course failure is greater than 90% (dropping out is also considered a failure), making submitting the first assignment a critical factor for predicting the final grade. However, considering that students' learning motivation largely depends on their demographic information, only submitting the first assignment is not enough to understand the different behaviour patterns of students and predict their learning motivation; their behavioural data and learning style recorded in the online learning platform system should be prioritized. Therefore, before submitting the first assignment, we analysed students' behavioural data, demographic information, assessment test information, and course registration information recorded in the virtual learning environment, such as homepage clicks, average clicks, forum clicks, etc.

This paper described the degree of participation of each variable in different categories through mean values (mean) and standard deviations (Std). The results show that students in the IMFS and UMS groups are more likely to delay submitting assignments than the other two groups. The large standard deviation values for both groups (Std = 12.11 and Std = 10.37) indicate that these students are weaker in time management and learning system control. Conversely, students in the IMPS and EMS groups have almost the same standard deviation, i.e., (Std = 8.91 and Std = 8.23), indicating that both groups always submit assignments at similar times or learn at a fixed rate. In the first assignment, the average scores for the IMPS, IMFS, EMS, and UMS groups are: mean = {70.55, 65.72, 79.91, 71.87}. It can be observed that the average score of students in the UMS group is higher than that of students in the IMFS group, indicating that UMS students had higher average grades and assignment scores from the beginning of the course to the submission of the first assignment. However, it is also concluded that students in the UMS group are more likely to delay submitting assignments, and as the course content becomes more complex, their interest in learning is more likely to be affected. Students in the EMS group have the highest average score in the first assignment and learn at a relatively stable pace during this period. These quantitative and other data analysis results are consistent with our previous analysis model of learning motivation.

From the average silhouette coefficient in Figure 2, the optimal number of Gaussians should be 2 clusters, as this yields the highest average silhouette coefficient value. However, according to the elbow rule, when k=2, the curve of the within-cluster sum of squares (SEE) does not show a rapidly decreasing trend. In other words, it is not an inflection point when k=2. But when k=3, the within-cluster sum of squares (SEE) sharply decreases, indicating an inflection point, and the average silhouette coefficient value at k=3 is relatively high, just slightly lower than the value at k=2. Therefore, when considering both the average silhouette coefficient and the within-cluster sum of squares, k=3 is the optimal choice for the number of clusters. The final results obtained in this paper are consistent with the motivation types defined by the SDT theory, indirectly proving the rationality and interpretability of this method.

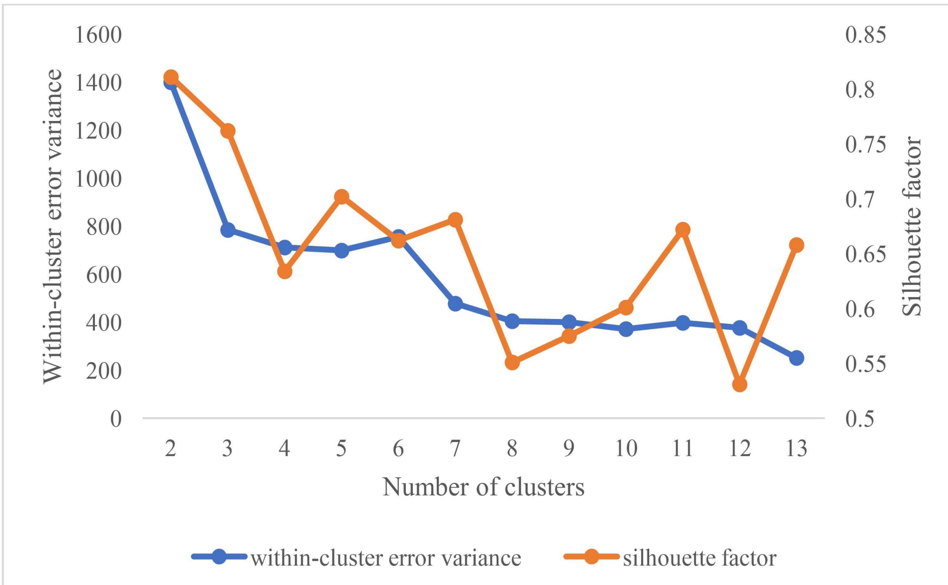


Figure 2. Impact of Within-Cluster Sum of Squares (SSE) and Silhouette Coefficient

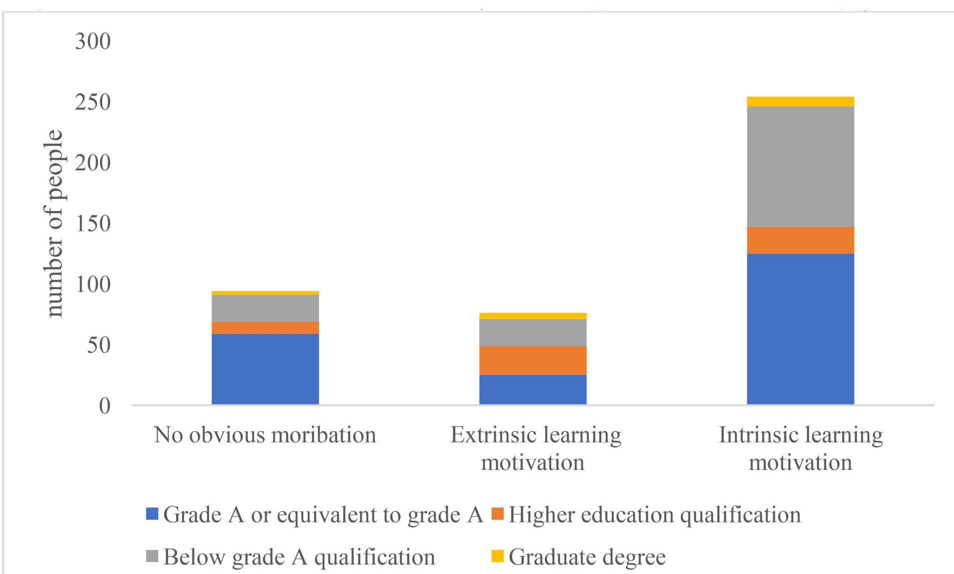


Figure 3. Distribution of Educational Levels Across Different Motivation Groups

In addition to the above content, this paper also analyzed the relationship between different educational levels and learning motivation. In this dataset, participants' educational levels are roughly divided into four categories: "A Level or equivalent qualification," "Higher Education (HE) qualification," "Below A Level," and "Postgraduate qualification." Figure 3 shows the distribution of students with different educational levels across different motivation groups. The figure shows that students with "A Level or equivalent qualification" and "Below A Level" educational levels account for about 70% of the total number of students. Students from all four educational levels are relatively evenly distributed in the group with extrinsic motivation. In the group with no clear motivation (no motivation), students with "Higher Education (HE) qualification" and "Postgraduate qualification" represent a small proportion of the total number of students, which aligns with the fact that students with higher educational levels tend to have stronger learning motivation or learning goals.

# 5. Conclusion

Understanding learning motivation combined with the Gaussian Mixture Model can help reform the system and methods of ideological and political education in universities and enable teachers to understand learners' learning progress and situations better. Accordingly, teachers can develop appropriate interventions for different learners based on specific issues, providing intelligent interventions for learners. This paper compares the participation characteristics of different motivation clusters, investigates the differences in course performance among students with different learning motivations, and explores the potential relationship between learning motivation and learners' educational levels.

The study demonstrated that students' learning behaviors are important indicators for identifying different learning motivations, and different learning motivations are significantly correlated with students' final ideological and political performance. Most students with intrinsic learning motivation showed higher performance in ideological and political learning, and even some students with unclear motivation also performed well. This may be related to other learning data not recorded outside the online learning platform, which could be further analyzed in future research. Based on demographic information and learning behavior clickstream data recorded in the virtual learning environment of the Open University, this paper proposed a Gaussian Mixture Model algorithm combined with Stacked Autoencoder (GMM-SAE). The maximum silhouette coefficient reached 0.82, and when the number of clusters was 12, the within-cluster sum of squares was less than 14, with the minimum value being 1.98.

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