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Correlation Structure Among Key Constructs in Online Blended Learning: A Multivariate Analysis

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ABSTRACT

The paper titled "Research on Gaussian Mixture Computational Learning Mode Based on MOOC Online Education" explores the integration of Gaussian Mixture Models (GMMs) and the Expectation Maximization (EM) algorithm into a blended learning framework centered on MOOCs (Massive Open Online Courses). The authors propose using GMMs to model complex learning behaviors and environmental variations, particularly in video based educational content, by distinguishing background (typical) from foreground (atypical) patterns. The EM algorithm is employed to estimate model parameters via iterative unsupervised learning, thereby improving convergence and adaptability compared to conventional methods such as K-means. The study also emphasizes a student centered blended learning approach, combining micro courses, MOOCs, VR/AR technologies, and social media platforms to enhance engagement and comprehension. An experiment involving a "Business Etiquette" course demonstrates that blended MOOC based learning increases student satisfaction, motivation, and outcomes, despite minor challenges like internet access or digital literacy. Simulations in MATLAB using synthetic Gaussian data validate the efficacy of the proposed computational model, demonstrating that adaptive learning rates and prior probability estimation significantly improve algorithm performance. The paper concludes that the GMM-EM framework offers a flexible, scalable solution for modeling educational data and optimizing online learning environments, advocating for careful parameter tuning to avoid ambiguity. Overall, the research bridges computational statistics and modern pedagogy to advance personalized, data driven online education.

Keywords: MOOC Online Education, Blended Learning, Gaussian Mixture Model (GMM), Expectation Maximization (EM) Algorithm, Student Centered Learning, Correlation Analysis, Latent Variables, Computational Learning

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1. Introduction

Every characteristic of the Gaussian distribution is established based on its individual weight and importance level, and by modifying the relevant thresholds, it is determined which features belong to the background distribution and which to the foreground distribution. Utilizing Gaussian distribution allows us to capture noise and environmental variations over several iterations more precisely. The Lee F1 technique enables us to implement this model in video surveillance and tackle challenges associated with subpar learning performance, particularly in intricate environments during the early training phase, as well as difficulties in shadow detection. To facilitate this, we increase the learning rate factor in the update equation to speed up convergence. However, since this learning rate factor operates at the global level, it lacks the ability to self adjust. Consequently, the Lee F1 technique integrates this factor with time to achieve self regulation of the learning algorithm for optimal outcomes. By consistently improving the algorithm's performance, we can significantly accelerate convergence [3].

By introducing the mixed Gaussian background model, we have created a high efficiency learning strategy. It posits that the distribution of current grayscale values is affected by a limited number of Gaussian distributions, and it can recognize them based on the weights assigned to these distributions, thereby enabling real time forecasting and processing of background data. With the EM algorithm, we can develop a background model based on recursive equations grounded in maximum likelihood estimation, thereby obtaining representations of learning and forgetting rates for normal conditions. Furthermore, we can employ an iterative method to fine tune these parameters for more precise results, thereby significantly enhancing the algorithm's convergence.

2. Related Work

By establishing a blended learning approach, we aim to improve learners' comprehension while effectively integrating their learning outcomes into daily teaching practices. To achieve this, we will utilize a variety of learning channels, such as micro courses and MOOCs, to offer a broader spectrum of instructional content. By aligning these resources with learners' specific needs, we can create a more integrated and rewarding learning experience. MOOCs merge traditional online educational materials with the internet, integrating state of the-art technologies and tools into physical classrooms. They are designed to help learners better understand the necessary knowledge and apply it comprehensively.

By leveraging VR, AR, and other advanced technologies, MOOCs foster a more realistic, immersive, personalized, rich, and holistic teaching environment. This helps learners grasp essential concepts and deepen their understanding of critical information. By utilizing internet technologies, such as offline discussion groups, WeChat public accounts, and fundamental video resources, we can efficiently manage learning and encourage open ended exploration through demonstrations, expert advice, and knowledge sharing, such as We Chat video broadcasts. This fully exploits the benefits of the internet, boosting awareness of online education while enhancing its functionality and reliability.

Despite the intricate theoretical basis and the challenge of local optima in Gaussian mixture algorithms, they continue to attract significant attention and research. To tackle these obstacles, Sub I has introduced several enhancement strategies from various angles to achieve improved outcomes. One practical approach to handle local optima is to utilize multiple initial values and choose the one with the highest likelihood function value

[6]. Although this method is relatively simple to execute, it demands additional effort and resources. K-means has been viewed as an alternative to the EM algorithm, offering superior starting points. However, due to its high initial values, K-means is less precise and cannot guarantee computational stability or reliability. Still, its user friendliness has made it a popular choice in many laboratories.

In addition to K-means, numerous other methods, such as deterministic annealing and genetic algorithms, can help laboratories obtain more accurate and efficient experimental data [7]. The benefits of "escaping" from the EM algorithm are clear, and while K-means can effectively improve system efficiency, the EM algorithm's ability to "escape" local optima remains widely preferred due to its slower execution speed [8]. Furthermore, strategies such as split and merge EM, component wise EMP, greedy learning, incremental versions, and parameter space grids have been proposed to enhance the EM algorithm, alongside other more efficient techniques aimed at boosting algorithm performance [9]. Nevertheless, the complexity of these methods or the insufficient examination of their potential drawbacks significantly hampers their adoption rate. Thus, research in this domain continues to pursue better results.

In Gaussian populations, Bayesian criteria, AIC, Markov chain Monte Carlo theory, resampling, and cross-validation present viable solutions for accurately identifying each Gaussian component [10]. Bayesian criteria can be used to estimate the overall population of Gaussian distributions, AIC can be used to estimate the total population, and Markov chain Monte Carlo methods can also aid in this estimation. In the context of micro-course video production and micro course classrooms, students should take on the central role. Therefore, educators should implement a student centred approach, dividing classroom time into two segments. The first half allows students to learn independently, while the second half focuses on teacher guidance and support, facilitating the application of various teaching methods within a limited timeframe. This approach encourages students to participate in the learning experience fully and fosters the development and efficacy of blended learning models in higher education..

3. Dataset and Methodology

3.1 Introduction to the Finite Mixture Gaussian Background Model

Through analysis, we found that when specific elements are located within similar geographic coordinate systems, their distributions follow Gaussian distributions. Therefore, we propose the use of a mixed Gaussian distribution, which has predictive power and accurately identifies elements in similar geographical coordinate systems. If, at a specific moment, a pixel's grayscale value is *X(t)*, then its probability of occurrence in the background model can be expressed by the following formula: The content of the formula is not provided in the text.

$$p = (X(t)) = \sum_{k=1}^{k} P\left(\omega_k(t)\right) \qquad (1)$$

In this sentence, *P*(og()) represents the predicted value of the k-th Gaussian element, reflecting the influence of this Gaussian element on the mixture distribution. o(I)={A(D), 4()} refers to the mean and covariance of the k-th Gaussian element, while t represents the probability density parameter of the Gaussian distribution.

$$\eta\left(X(t)| \ \omega_k(t), \theta_k(t)\right) = \frac{1}{(2\pi)^{n/2} |\Sigma|^{1/2}} \qquad (2)$$

If p(X(t)) exceeds a certain threshold T, then we can determine that the pattern follows the background distribution. If *K*=3, then this pattern will be classified into Friedman and Russell's background pattern. Stauffer and Grimson [2] used the Gaussian B to construct the background model: setting argmin(*P*(og(Tn))) to a certain threshold, a new result - K) can be obtained when *P*(og(X))=0, (k-B+1). This model, derived from Stauffer and Grimson, employs finite Gaussian mixtures as a framework to describe complex mathematical phenomena. By adopting the maximum likelihood method, unsupervised learning problems can be transformed into classical parameter estimation problems in probability theory. The core idea of the maximum likelihood method is that when the distribution of samples conforms to the expected pattern, their probabilities will be maximized, resulting in more accurate predictions. Therefore, to achieve the best results, we should precisely select the parameters of the probability density function to maximize the joint density of the samples. Using the maximum likelihood estimation, we can express more clearly how to obtain effective results. For example, if the distribution of samples is composed of one dimensional Gaussian distribution *P(X)*=G(X, μ σ^2), then ì and σ^2 are the parameters to be estimated, representing the mean and variance of the Gaussian function, respectively. Generally, to obtain the desired parameters, we need to establish the corresponding likelihood function.

$$L\left(\mu,\sigma^2\right)=\prod_{i=1}^{n}\frac{1}{\sqrt{2\pi\sigma}} \qquad (3)$$

Even when using GMM to model data as a mixture of Gaussian distributions, it is still not possible to meet the requirements. Therefore, to accurately calculate the analytical results for each parameter, more complex strategies must be adopted, such as using the mixture Gaussian distribution (1) or the mixture Gaussian (3). In general, EM algorithm (Expectation-Maximization) can be utilized to estimate the required parameters intuitively. Thus, this paper will delve into the application of the EM algorithm.

3.2 Introduction to EM Algorithm

The basic assumption of the EM algorithm is that the dataset is complete, including *X, Y,* and the labeled data {*Y'*, ..., Y_s}, where *Y'* represents a binary vector with elements taken from {0,1}, and *q*=1,...,*k*, q_{tp} are taken from {0,1}, such that when the i-th data point comes from the p-th Gaussian component of the GMM model, *y*=1, otherwise *y*=0 [11, 12]. With the given dataset, we can construct a likelihood function called the E-step, which predicts the probabilities of the latent variables *Y* to achieve the desired outcome. Under the "conditional" assumption that *X* and *Y'* are known, c represents a set of new parameters that together form a

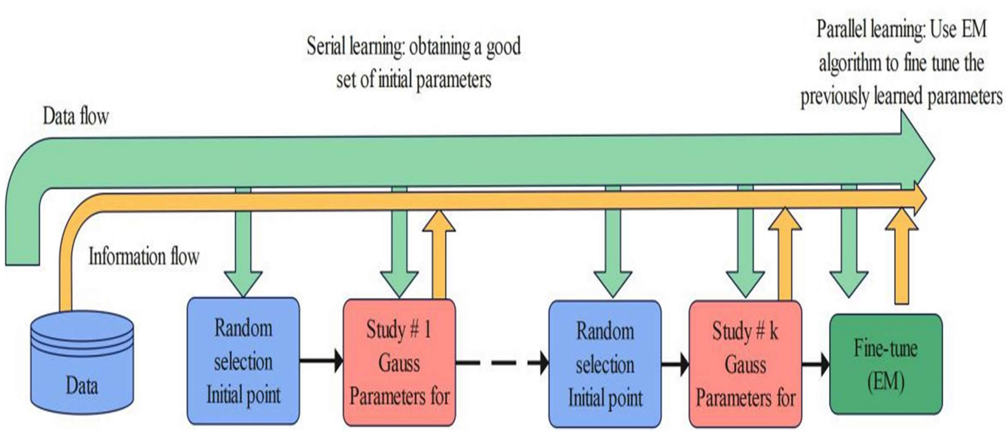

Figure 1. Algorithm Structure Diagram

complete model to describe the relationship between the observed data X and the current parameters *Y*'. In comparison to traditional methods based on the likelihood function for parameter estimation, the *EM* algorithm emphasizes the importance of finding the auxiliary function Q [13, 14]. Therefore, the likelihood function of the *EM* algorithm must be based on the dataset of *X* and *Y*, and also consider the latent factors in the dataset, i.e., the storage of *Y*, to effectively convert it into a statistic and reduce the adverse effects caused by *Y*. This effort is made to seek more possibilities while discovering and utilizing these latent opportunities to reduce unforeseen risks, as shown in Figure 1.

Clearly, the EM algorithm starts with a set of initially set parameters and estimates the probabilities of each data point belonging to each Gaussian component based on these parameters, resulting in an artificially obtained labeled dataset. Here, each data point is probabilistically assigned to each element, yielding a soft assignment. Once we have these labeled databases, the problem becomes simplified, and unsupervised learning is transformed into supervised learning. Supervised learning is a learning process with annotations, meaning that we not only obtain data points but also know which Gaussian components (or with what probabilities) generated them [15, 16]. Then we can handle data collection accordingly. For each element of the Gaussian function, we estimate its parameters using the points belonging to that component. Each data point is weighted by its probability of belonging to that component. In this way, we complete one round of updates for the parameter set. We repeat this process iteratively, based on the newly added parameters, until there are no significant changes in the parameters between successive iterations.

4. Experimentation and Results

4.1 Experimental Model

This study utilized a blended learning approach with MOOCs and conducted a survey among students studying "Business Etiquette." The learning environment at the school was excellent, and the WiFi system supported all teaching activities seamlessly. During the blended learning practice, we observed that all learners were proficient in using computers and mobile devices. Additionally, many researchers were familiar with MOOCs and used them when studying specific subjects. In the final stage of this practice, we collected feedback from the researchers via questionnaires on their satisfaction, sense of achievement, enjoyment, and learning experiences. We hope this information can assist more researchers in achieving better results in blended learning practice. Through blended learning with MOOCs, students' engagement significantly improved, and their learning interests were stimulated. With the widespread use of smartphones, most learners appreciated the blended learning mode with MOOCs and considered it to yield good learning outcomes. Although some students, particularly minority students, might encounter challenges in blended learning, such as network latency, limited computer skills, and other difficulties, they still benefit from valuable guidance, including timely feedback, effective communication, reasonable study arrangements, and collaborative learning in study groups. By adopting the blended learning mode, we could utilize its diverse assessment methods and provide rapid and accurate feedback, enabling us to understand learners' learning statuses better and flexibly adjust classroom content according to actual situations, thereby achieving better learning outcomes.

4.2 Analysis

Using random numbers generated from a mixed Gaussian distribution can better simulate the visual effects in the field. Next, we constructed digital Gaussian distribution learning algorithms and corresponding image processing algorithms using MATLAB and Direct show to evaluate the effectiveness of the algorithm. By analyzing a mixed Gaussian distribution consisting of 1000 independent Gaussian distributions, we found that their means were 200, 100, and 10, respectively, while their variances were 1, 4, and 9, and their prior probabilities were 0.2, 0.3, and 0.5, respectively. According to Figure 2, we can observe a large number of data samples.

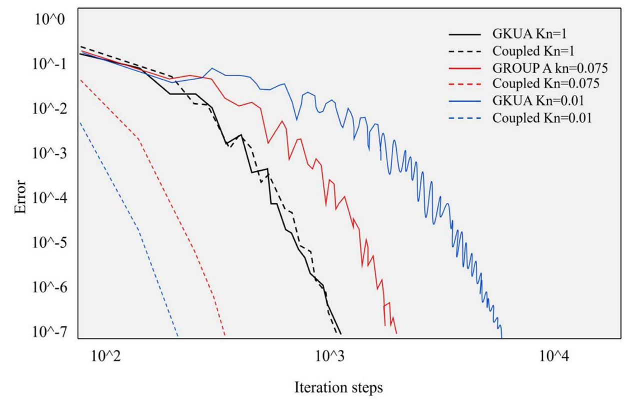

Figure 2. Differences in the convergence rate of variance mean between the two schemes

By utilizing α= The parameters of the mixed Gaussian distribution (mean and variance) set at 0.02 are employed in this research α The method is integrated with the y of this study to handle data samples in the form of a mixed Gaussian distribution. As illustrated in Figure 2, the convergence outcomes of the mixed Gaussian distribution are observable, where α The dashed line representing the scheme corresponds to 1, while the dashed line of the y scheme indicates y, both leading to a mean measurement of 0.02 and a variance of 0.02.

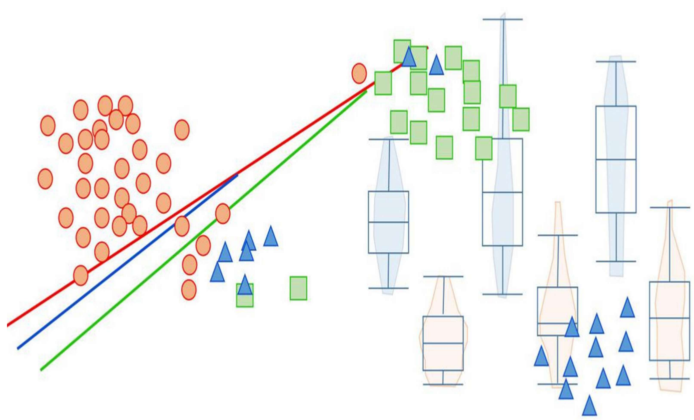

Figure 3. Convergence Average of Prior Probabilities for Gaussian Distributions

Figure 3 shows that the prior probabilities for the Gaussian distributions α and y are roughly 20 and 1, respectively. This suggests that when the prior probabilities for both α and y reach a specific threshold, they converge rapidly to their true values, facilitating the effective acceptance of the prior distributions for both α and y. The α method requires about 150 data points, rendering it less efficient in terms of convergence performance compared to the α method. Although the α scheme demonstrates slower convergence and lower accuracy than the 1 scheme, its learning rate, α=0.02, significantly simplifies its complexity. In contrast, the one scheme offers a simpler model structure, requiring only a portion of the original data to be retained. Comparatively, the α scheme offers a more adaptable model structure, making it more flexible and easier to scale, and thus better suited to a multivariate setting. Accurate calculations allow the exclusion of data that exceeds the predefined threshold, eliminating the need to retain all original data and significantly reducing the system's resource consumption.

5. Conclusion

The development of a blended learning model in MOOCs aims to continually refine course content and methodologies, helping students better understand the material and achieve self directed learning. This blended learning strategy is more aligned with contemporary social progress, promoting educational reform and enhancing students' learning experiences. Based on the principle of maximum likelihood, we introduce the recursive equations for mixed Gaussian simulation and present the EM algorithm. Through detailed investigation, we discover that this algorithm exhibits superior convergence properties compared to conventional methods and has a considerably broader application range. Furthermore, its parameter configurations are more adaptable, enabling modifications based on real world conditions. However, esta- blishing current objectives at excessively high or low levels may lead to parameter ambiguity and diminish the focus on foreground targets. Hence, future researchers should be mindful of such situations to more effectively achieve their goals.

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