Remittances Review
May, 2023
Volume: 8, No: 3, pp. 125-142
ISSN: 2059-6588 (Print) | ISSN 2059-6596 (Online)

Received: 11 November 2022 Accepted: 27 March, 2023
DOI: https://doi.org/10.33182/rr.v8i3.9

Analysis of the difference in the development of advertising education between Chinese and Thai universities based on ELM algorithm

Yuwen Zhao [1] Ping Jiang[1]

Abstrac

Analyzing the differences in the development of advertising education between Chinese and Thai universities can bring insights into the development direction of advertising education in China. In this article, we examine the theoretical foundations of the single hidden layer feedback neural network-based extreme learning machine algorithm. To address the challenge of SLFNs' lengthy training times, iteration is used to continuously adjust the input weights and bias vectors of the hidden units. Meanwhile, due to the poor generalization ability of the ELM algorithm, the Mercer condition is used to construct the kernel matrix instead of the output matrix to establish the ELM model with kernel function, and the difference in the development of college advertising education between China and Thailand is analyzed based on the KELM algorithm.From 2011 to 2018, the percentage of advertising practitioners with education at bachelor's degree and above in China has increased by 14.5%, and that in Thailand is 17.6%. The teacher-student ratio of advertising education in Chinese universities has improved by nearly 700% from 2001 to 2020, while Thailand has improved by nearly 3000%. Meanwhile, the overall evaluation index of advertising teaching in Thai universities has improved by 22.93% since entering the new century, and China has also improved by 19.84%. Based on ELM's analysis of the real situation and developmental differences of advertising education in each country in the new era, it can provide a perspective for observation and consideration of college advertising education, which is expected to be reformed.

Keywords: *KELM algorithm; single hidden layer feedback; kernel function; college advertising education*

Introduction

Since the first modern commercial advertisement in China appeared in 1979, the first major in advertising in China was founded in the Department of Journalism and Communication of Xiamen University in 1983 with approval of Ministry of Education. Subsequently, in the fall of 1993 and 1995, the advertising majors of the Department of Journalism of Beijing Broadcasting Institute and the Department of Journalism and Communication of Xiamen University began to enroll master's students in the graduate direction of advertising, respectively (Yan Q F, 2016) (She S, 2018). Advertising education in China has been moving forward under the urging and coercion of advertising development, going through the fumbling period, initial period, development

[1]Associate Professor, Department of Management, College of Business Administration, King Faisal University, Al-Ahsa 31982, Saudi Arabia.
Corresponding author: Yuwen Zhao (13408522747@163.com)

Volume: 8, No: 3, pp. 125-142
ISSN: 2059-6588 (Print) | ISSN 2059-6596 (Online)

period and take-off period, until it has come to a dazzling new situation. Eventually, the situation of joint development of multiple modes of education such as correspondence education, self-study examinations, radio and television universities, professional and technical certification examinations and job training, in addition to full-time school education, has been formed, gradually forming an all-round, multi-level and multi-category advertising talent training pattern (Alhabash, 2021)-(Ma, 2021).

On the one hand, the quantitative increase of higher advertising education has brought many problems such as mass advertising education, mediocre advertising effect and high education and low level, which makes the graduates of advertising majors also face the pressure of employment, while on the other hand, large advertising companies are constantly in the crisis of talent shortage, and the imbalance between the development of economy and education level leads to the inefficiency of most higher advertising education (Zhang Y, 2019) (Liu, 2021)-(Hwang, Yum, & Jeong, 2018).As a force to support the development of advertising industry, advertising education should respond positively to the development of advertising practice and show forward-looking thinking to cultivate more talents who are in line with the development of the industry. However, the traditional advertising education model and curriculum are set according to the advertising agency system, and nowadays the traditional advertising agency industry is seeking changes under the impact of new media, consequently, the conventional advertising education model cannot be modified to meet the demands of the modern world.

Research results on advertising and advertising education are abundant and have continued to heat up in recent years. The literature (Hou J, 2015) analyzes the characteristics and rules of advertising education in the United States, Britain and Japan in terms of educational philosophy, professional affiliation, curriculum and faculty, etc., and proposes future development directions in the light of the current situation of advertising education in China.

According to the literature (Zhao & Ji, 2019),advertising is a significant discipline that may communicate and explore new viewpoints as well as reflect how an audience feels about morality, aesthetics, consumerism, and societal developments. Literature (Jing B, 2018) proposed that new changes have occurred in the advertising business in the new media environment, and thus the objectives of advertising talent training and college teaching should be reformed accordingly, and through reflecting on the problems and shortcomings in the practical teaching mode, a new concept of practical teaching was proposed.

The literature (Zha C C, 2016) conducts in-depth evaluation and research on the established curricular framework and faculty organization of American colleges and institutions' advertising education, pointing out that the curriculum system is the core of the modern discipline, which can directly reflect the professional quality, teaching level and development mode of the discipline, and puts forward suggestions for the development of advertising in China.

The literature (Kaewkatorn, 2013),on the other hand, conducted a study on advertising students

May, 2023
Volume: 8, No: 3, pp. 125-142
ISSN: 2059-6588 (Print) | ISSN 2059-6596 (Online)

at the University of Isaac, Thailand, and analyzed the relationship between students' personalities and academic performance through a survey study, proving that there was no significant correlation between personality differences and performance of advertising students. The literature (Morimoto, 2019) studied the challenges faced by Japanese advertising education facets in the era of globalization, and proposed ways to respond to them by analyzing the deeper causes of these challenges.

The literature (L, 2019) argues that the advertising industry is undergoing structural changes and advertising education faces daunting challenges in keeping up with the real world, and argues that universities should bridge the gap between academia and industry and make changes to the traditional advertising education system. The literature (Chang C, 2018) investigated and studied the teaching reform and practice of undergraduate advertising education in Anhui University of Finance and Economics, and concluded that only by closely linking and updating the teaching ideas and methods of advertising with the development of the advertising industry can students' theoretical level, innovation awareness and practical ability be effectively improved.

The extreme learning machine model is established in this paper by continuously adjusting the input weights and bias vectors throughout the training process, and the weights from the hidden layer to the output layer are obtained by using the least squares method. The method principle of SLFNs is explored, and the mapping function is established to train the sample set. In order to address the issue of unsatisfactory generalization ability and stability brought on by the randomly assigned parameters of the hidden layer, the kernel function is introduced into the ELM model for the scenario in which the feature mapping of the hidden layer is unknown. The random mapping in the basic ELM is replaced by the kernel mapping.

Finally, the evaluation indices of college advertising education and the training sample set of KELM are produced by contrasting and examining the development histories of college advertising education in China and Thailand. Finally, based on the KELM algorithm, we analyze the education distribution of advertising practitioners in China and Thailand, the faculty strength of colleges and universities, and the comprehensive evaluation index of teaching based on the evaluation dimensions of training objectives, training specifications, curriculum system, and quality assurance mechanism, and provide sound recommendations for the growth of China's advertising education.

Extreme learning machine algorithm and its improvement

Extraordinary Learning Machine

Neural network with a single hidden layer of feedback

From Single Hidden Layer Feedback Neural Networks, Extreme Learning Machines (ELMs) have developed (SLFNs). Artificial neural networks, or neural networks for short, are a mathematical model that is based on the central nervous system of animals and has the capacity

Volume: 8, No: 3, pp. 125-142
ISSN: 2059-6588 (Print) | ISSN 2059-6596 (Online)

to learn and detect patterns. They are extensively used in computer science and related subjects.

A neural network may be seen as a collection of interconnected neurons, with a neuron serving as the network's smallest unit. Most of the time, a neuron may alter itself in response to input from outside information, making the entire brain system adaptable. Modern neural networks are a nonlinear statistical data modeling tool that are frequently used to investigate data patterns or represent complicated interactions between inputs and outputs.

The entire neuron model is expressed mathematically as $y = g(w \cdot x + b)$, where g is the neuron's excitation function, which is typically a nonlinear function of $R \to R$. Generally, $traingd(\cdot)$, $tansig(\cdot)$, $sigmoid(\cdot)$, etc. are available. $w \cdot x$ is the inner product of vectors w and x. It follows that a neuron's job is to produce a scalar output response by applying a nonlinear excitation function to the inner product of the input vector, the input weights, and the bias sum. Figure 1 displays a single hidden layer feedback neural network with a $n-L-m$ topology.

The input layer, which can collect information from the outside world, the hidden layer, which has no link to the outside world, and the output layer, which can give feedback to the outside world, make up the three layers of neurons that make up the total neural network.

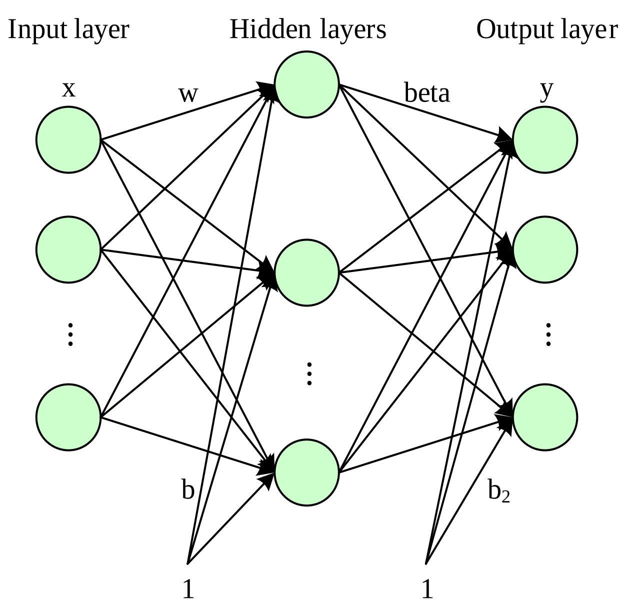

Figure 1 Neuronal schematic diagram

The SLFN model descriptors are included in Table 1 for ease of explanation.

Volume: 8, No: 3, pp. 125-142
ISSN: 2059-6588 (Print) | ISSN 2059-6596 (Online)

Table 1 Descriptor of the SLFN model

Symbol	Meaning
N	total samples used for training
L	The quantity of items in hidden layers
d	the number of dimensions in the input vector, or the number of input layer components
m	The quantity of output layer components, or the output vector's dimensions
$x_j = \left(x_{j1}, x_{j2}, L, x_{jd}\right)^T \in R^d$	Input vector
$t_j = \left(t_{j1}, t_{j2}, L, t_{jm}\right)^T \in R^m$	Output labels, which are ideal outputs
$\left(x_j, t_j\right), j = 1, 2, K, N$	Training samples
T	Output matrix
$g(x)$	Activation function

The general excitation functions of the input layer and the output layer in a typical single hidden layer feedback neural network are both set to a linear function of $g(x) = x$. Thus, the response of the nd neuron in the output layer may be written as follows:

$$y[k] = \left[g\left(w_1 \cdot x + b_1\right) \quad g\left(w_2 \cdot x + b_2\right) \quad \cdots \quad g\left(w_L \cdot x + b_L\right) \right] \cdot \beta_k + b_2[k], k = 1, \ldots, m \tag{1}$$

Where, $w_i \in R^n, i = 1, \ldots, L$ stands for the input weight, also known as the input, of the ind neuron in the buried layer. The output weight, or input weight, of the kth neuron in the output layer is represented by the symbol $\beta_k \in R^L, k = 1, \ldots, m$. The following equation can conveniently express the entire single hidden layer feedback neuron:

$$y = h(x)\beta + b_s \tag{2}$$

where $y \in R^m$ is the collective response of each neuron in the output vector (also known as the output layer) of the neural network.

The hidden layer response vector, abbreviated as $h(x) = \left[g\left(w_1 \cdot x + b_1\right) \quad g\left(w_2 \cdot x + b_2\right) \quad \cdots \quad g\left(w_L \cdot x + b_L\right) \right]$, represents the collective response of all neurons in the neural network's hidden layer to the input vector x.

The output weight matrix, often known as $\beta = \left[\beta_1^T \quad \beta_2^T \quad \ldots \quad \beta_m^T \right]^T$, is a matrix that organizes all of the neural network's output weights.

The hidden layer's i nd neuron's bias is b_i, while the output layer's entire vector's bias is represented by $b_s \in R^m$. The transpose operation of the matrix is represented by T.

It is evident from Eq. (2) that the neural network really creates a mapping function $f : x \rightarrow y$ and represents the hitherto abstract mapping function f in the concrete form of Eq (2). By adjusting the neurons' input weights, the neural network may theoretically represent any mapping function f.

The capacity of a mathematical model to learn is what we are most interested in when it comes to machine learning. Learning entails locating the function in the function space F that, when applied to the training sample set $\{x_j, t_j\}_{j=1}^N$, minimizes the loss function C. where $x \in R^n$, called the features of the sample, and $x \in R^m$, called the labels of the sample.

The frequently used loss function based on the Euclidean distance may be stated by the following equation. The loss function C is a highly significant notion in machine learning and is a concept that expresses the measure of the mathematical model vs the real observation:

$$C = E\left[\| f(x) - t\|_2\right], (x,t) \in D \qquad (3)$$

where E denotes the expectation, D denotes the sample space, and $\|\cdot\|^2$ denotes the 2-parametric operation of the matrix.

In practice, we can only obtain a fraction of samples in the sample space D, so in practical applications we use equation (4) instead of equation (3).

$$C = \frac{1}{N} \sum_{j=1}^{N} \left\| f\left(x_j\right) - (t)_j \right\|^2 \qquad (4)$$

The compact version of equation is obtained by substituting equation (2) into equation (4):

$$C = \left\| T - \left(H\beta + b_s \otimes 1_N \right) \right\|_F \tag{5}$$

Among them, there are:

$$T = \begin{bmatrix} t_1 \\ t_2 \\ \vdots \\ t_m \end{bmatrix}_{L\times m} \tag{6}$$

$$H = \begin{bmatrix} h(x_1) \\ h(x_2) \\ \vdots \\ h(x_N) \end{bmatrix}_{N\times L} \tag{7}$$

T is a matrix of the labels of the training samples t_j arranged so that each row represents a training sample label t_j. H is a matrix of the responses of the features of the training samples in the hidden layer $h(x_j)$ arranged so that each row represents the hidden layer response of a training sample $h(x_j)$. $\otimes$ represents the Kronecker product operation and $1_N \in R^N$ represents a column vector with all elements being one.

Therefore, the learning process of a neural network can be described in the following mathematical language: on the training sample set $\{x_j, t_j\}_{j=1}^N$, find the w_i, b_i, β, b_s that minimizes the loss function C. The learning process can be expressed by the following equation:

$$w_j^*, b_j^*, \beta^*, b_s^* = \underset{w_j, b_j, \beta, b_s}{\arg\min} \left\| T - \left(H\beta + b_s \otimes 1_N \right) \right\|_F \tag{8}$$

The core of the backpropagation algorithm lies in the application of the chain rule of derivation, according to which the backpropagation algorithm makes the following transformations:

$$\frac{\partial C}{\partial w_i} = \frac{\partial C}{\partial h_i} \frac{\partial h_i}{\partial w_i} \tag{9}$$

$$\frac{\partial C}{\partial b_i} = \frac{\partial C}{\partial h_i} \frac{\partial h_i}{\partial b_i} \tag{10}$$

where $\frac{\partial}{\partial}$ denotes the partial derivative operation.

The error back propagation algorithm first calculates the gradient in the solution process, then calculates the sum according to the gradient formula, and finally updates the output weight β, output bias b_s, input weight w_i and bias b_i. The proposer Rumelhart creatively refers to this process as the error back propagation process; it is analogous to adding a feedback layer to a single hidden layer neural network, thus the term single hidden layer feedback neural network. The name "single-hidden layer feedback neural network" refers to the analogous process of adding a feedback to a single-hidden layer neural network.

Extreme Learning Machine

Single-hidden-layer feedback neural networks possess the following two comparatively exceptional qualities: (1) They are able to directly fit complicated mapping functions $f: x \to t$ using training samples. (2) They are able to offer models for several man-made or natural events that are challenging to address using conventional classification parameter procedures. Single hidden layer feedback neural networks don't have a very quick learning mechanism, though. Iterations of the error back propagation technique necessitate updating the $n \times (L+1) + L \times (m+1)$ values, which takes considerably less time than is acceptable. It is common to observe that training a single hidden layer feedback neural network takes hours, days, or longer.

For SLFNs, the usual learning algorithm uses an iterative approach to continuously adjust input weights W and bias vector of the hidden cell b. In fact, extensive experimental results show that the parameters W and b of SLFNs do not need to be adjusted and can be specified arbitrarily. The optimal weight of the equation is the least-squares solution of the linear system with fixed W and b, i.e.

$$\| H\hat{\beta} - T \| = \min_{\beta} \| H\beta - T \| \quad (11)$$

Its minimum parametric least squares solution is:

$$\hat{\beta} = \arg\min_{\beta} \| H\beta - T \| = H^{+}T \quad (12)$$

Weight β has the smallest parametric value as well as the best generalization ability. Among all the equation's least squares solutions, β has the lowest parametric number, and is therefore called the least squares very small parametric solution. Additionally, the generalization capacity of SLFNs is inversely correlated with the order of magnitude of the weights; the lower the order of magnitude, the greater the generalization ability.

Unlike the gradient descent-based BP algorithm that requires constant adjustment of weights among all layers, ELM does not iteratively update the weights of the input and hidden layers of SLFN, which are set and fixed on the fly (Fianu, 2022)-(Rastgou, Bayat, Mansoorizadeh, & Gregory, 2022). Without any configuration or iterative modification, the weights of the hidden layer to the output layer are obtained by solving the ELM using least squares. As a result, the ELM algorithm requires less human interaction, trains very quickly, adjusts network parameters quickly and easily, and has better generalization abilities. Figure 2 displays the Extreme Learning Machine network.

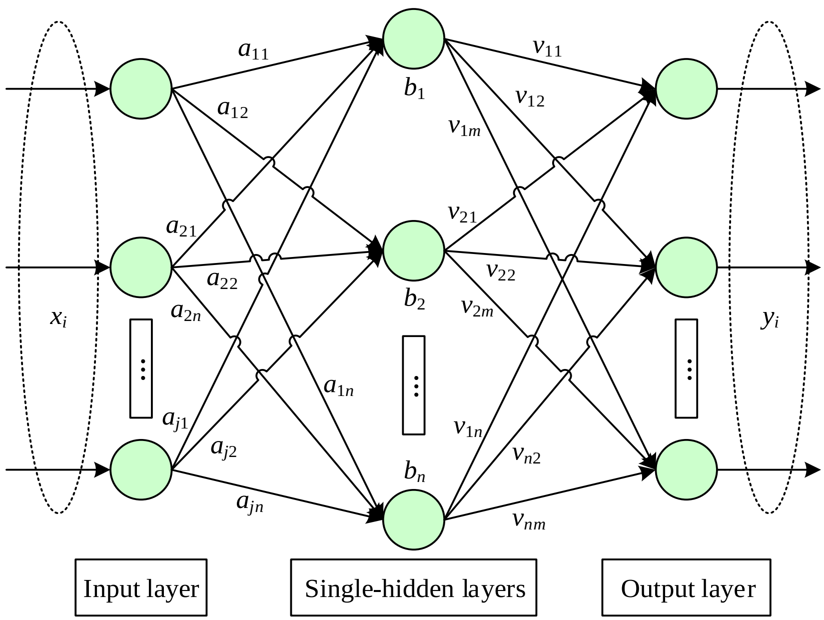

Figure 2 Extreme learning machine network structure

A regularization factor $\frac{1}{\lambda}$ is generally added to the diagonal of $H^T H$ or HH^T to obtain a more stable and better generalization capability, and the output matrix is denoted as:

$$\beta = H^{+}T = \begin{cases} H^T\left(\frac{I}{\lambda} + H^T H\right)^{-1} T \\ \left(\frac{I}{\lambda} + H^T H\right)^{-1} H^T T \end{cases} \tag{13}$$

Table 2 displays the precise steps of the ELM algorithm.

Volume: 8, No: 3, pp. 125-142
ISSN: 2059-6588 (Print) | ISSN 2059-6596 (Online)

Table 2. Specific steps of the ELM algorithm

Input	Training sample $\aleph=\left\{\left(x_i,t_i\right) \mid x_i\in \mathrm{R}^d,t_i\in \mathrm{R}^m,i=1,\ldots,N\right\}$, the output function of the hidden layer node $G\left(\alpha_i,b_i,x\right)$, the number of hidden layer nodes L.
Step 1	Randomly generate the hidden layer node parameter $\left(\alpha_i,b_i\right),i=1,\ldots,L$
Step 2	Calculate the hidden layer output matrix $H=\begin{bmatrix} h\left(x_1\right) \\ M \\ h\left(x_N\right) \end{bmatrix}=\begin{bmatrix} G\left(\alpha_1,b_1,x_1\right) & L & G\left(\alpha_L,b_L,x_1\right) \\ M & L & M \\ G\left(\alpha_1,b_1,x_N\right) & L & G\left(\alpha_L,b_L,x_N\right) \end{bmatrix}_{N\times L}$
Step 3	Calculate the optimal output weight $\beta=H^{+}T=\begin{cases} H^T\left(\frac{I}{\lambda}+H^TH\right)^{-1}T \\ \left(\frac{I}{\lambda}+H^TH\right)^{-1}H^TT \end{cases}$
Output	Objective function $f(x)=h(x)H^{\mathrm{T}}\left(\frac{I}{\lambda}+HH^{\mathrm{T}}\right)^{-1}T$

Nuclear Limit Learning Machine

The kernel function is included into the ELM and the kernel limit learning machine (KELM) is presented on the basis of the learning concept of the support vector machine. The kernel function based on ELM is examined by employing Mercer's condition to generate the kernel matrix rather than HH^T in the scenario when the feature mapping of the hidden layer is unknown:

$$\Omega_{EZM}=HH^{\mathrm{T}}:\Omega_{EZM,j}=h\left(x_i\right)\cdot h\left(x_j\right)=K\left(x_i,x_j\right) \tag{14}$$

$$HH^{\mathrm{T}}=\Omega_{ELM}=\begin{bmatrix} K\left(x_1,x_1\right) & L & K\left(x_1,x_N\right) \\ M & 0 & M \\ K\left(x_N,x_1\right) & L & K\left(x_N,x_N\right) \end{bmatrix} \tag{15}$$

$$h(x)H^{\mathrm{T}}=\begin{bmatrix} K\left(x,x_1\right) \\ M \\ K\left(x,x_N\right) \end{bmatrix}^T \tag{16}$$

As a result, the ELM output equation may be written as:

$$f(x)=\begin{bmatrix} K(x,x_1) \\ M \\ K(x,x_N) \end{bmatrix}^T \left(\frac{I}{\lambda}+\Omega_{ELM}\right)^{-1} T \tag{17}$$

The kernel function corresponding to the implicit layer feature mapping is provided in this version of the ELM method, therefore it is not necessary to understand the implicit layer feature mapping. A number of implicit layer nodes need not be specified (which indicates the dimensionality of the implicit layer feature space). The kernel limit learning machine algorithm's input and output are therefore obtained as follows:

Input: Training sample $\aleph=\{(x_i,t_i)|\ x_i\in\mathrm{R}^d, t_i\in\mathrm{R}^m, i=1,\ldots,N\}$, kernel function $K(u,v)$.

Output: Target equation $f(x)=\begin{bmatrix} K(x,x_1) \\ M \\ K(x,x_N) \end{bmatrix}^T \left(\frac{I}{\lambda}+\Omega_{ELM}\right)^{-1} T$.

The issue of subpar generalization ability and stability brought on by the arbitrarily chosen parameters of the implicit layer is significantly addressed by adding the kernel function to the extreme learning machine and swapping out the random mapping in the basic ELM with the kernel mapping. Additionally, it greatly decreases computational cost, avoids optimizing the number of nodes in the hidden layer, and is able to produce the least-square optimal solution, which outperforms the support vector machine and basic ELM algorithms in terms of stability and generalization. Therefore, classification and regression issues frequently involve the usage of kernel limit learning machines.

Chinese and Thai universities' developments in advertising education are compared.

Development of Advertising Education in China

The 1920s saw the introduction of the first advertising courses in China, which were provided as parts of journalism studies at several colleges. In 1918, the Journalism Research Association established in China began to include advertising as a study part of journalism. from 1920 to 1925, advertising was offered as a course at St. John's University in Shanghai, Xiamen University, Beijing Civil University, Beijing International From 1920 to 1925, advertising was offered as a course at St. John's University in Shanghai, Xiamen University, Beijing Civil University, Beijing International University, Yanjing University.

And the Department of Newspaper Studies of Southern University in Shanghai, but it was limited to the study of newspaper advertising. Advertising education in early China did not become an independent discipline; it was only a component of journalism education, so it was not advertising education in the strict sense; the real sense of advertising education came after the reform and opening up. Table 3 charts the evolution of advertising education in China following reform and opening.

Table 3 China's advancement of advertising education

Get on track	80s of the 20th Century	The introduction of communication laid the foundation for advertising education.
	Early 90s of the 20th Century	Colleges and universities began to establish advertising majors.
A period of great development	Late 90s of the 20th Century	The great development of the advertising industry has greatly increased the demand for advertising talents. There are about 90 universities with advertising majors.
Transition	In 2015	The Ministry of Education has launched a pilot reform of local undergraduate colleges to application-oriented colleges.
	In 2019	The number of advertising majors has not been greatly affected, but the number of advertising majors in colleges and universities has slowed down significantly.

Development of Advertising Education in Thailand

Education in advertising is a branch of communication arts education in Thailand. Communication arts education in Thailand began in 1939 when Chulalongkorn University began offering communication arts courses in the College of Arts and Sciences, focusing on newspaper-related studies and offering an associate degree. The first to offer a bachelor's degree in communication arts was offered by Hossein University, followed by Chiang Mai University, Mahidol University, Oriental University and more and more universities, whose main purpose was to train journalists for government or business. Because political figures needed to form influence through the media, communication arts education in early Thailand had a strong relationship with politics. Since then, the scope of communication arts education has gradually expanded, and advertising has appeared in the curriculum of communication arts education.

Over time, the scope of communication arts education expanded, leading to the inclusion of advertising as a subject in the curriculum. As the significance of advertising grew, universities recognized its importance in the communication landscape and incorporated it into their educational programs. Advertising education within communication arts programs helps students develop a comprehensive understanding of the principles, strategies, and techniques involved in

May, 2023
Volume: 8, No: 3, pp. 125-142
ISSN: 2059-6588 (Print) | ISSN 2059-6596 (Online)

creating effective advertisements and managing advertising campaigns. As the advertising industry evolved and gained prominence in Thailand, communication arts education continued to adapt to the changing needs of the field. The curriculum expanded to cover various aspects of advertising, including market research, consumer behavior analysis, creative concept development, media planning, and advertising management. Through these programs, aspiring professionals in advertising receive the necessary theoretical knowledge and practical skills to thrive in the industry. Today, communication arts education in Thailand encompasses a wide range of disciplines, including journalism, public relations, mass communication, broadcasting, film and television production, and advertising. These programs provide students with a comprehensive education in communication and media-related fields, equipping them with the skills and knowledge needed to succeed in various careers within the industry.

Advertising education in Thailand originated from the emergence of communication studies in Thailand. The development of advertising education in Thailand can be divided into four periods: the Formative Period, the Leap Period, the Boom Period, and the Modern Period. Its specific development history is shown in Table 4.

Table 4 The development of advertising education in Thailand

Formative period	30s of the 20th Century	Chulalongkorn University and Thammasat University began to establish newspaper-related course content.
	Early 70s of the 20th Century	Thammasat University upgraded the Department of Journalism to an independent School of Journalism and Mass Communication. Advertising courses become part of the study of independent faculties.
Leap Forward	Since 1976	The membership of the Thai Advertising Business Association has gradually increased, and with it, its size.
	In 1977	TACT Awards are founded.
	From 1977 to 1981	Advertising gradually broke away from public relations and became an independent discipline.
Boom period	From 1988 to 1997	Universities that are already teaching in the field of advertising are actively reforming the structure and content of their courses.
		Private colleges and universities have also begun to offer advertising majors.
		Four universities offer advertising courses at the postgraduate level.
Modern period	From 1998 onwards to the 21st Century	The use of information technology and the emphasis on scientific and technological talents have influenced advertising education in Thailand.

Remittances Review
May, 2023
Volume: 8, No: 3, pp. 125-142
ISSN: 2059-6588 (Print) | ISSN 2059-6596 (Online)

Results and analysis

This article compares the historical evolution of advertising education in China and Thailand and then contrasts them in three areas: practitioners' credentials, assessment of advertising teaching, and faculty strength based on the KELM algorithm.

KELM-based practitioner education analysis

A comparison of the educational distribution of advertising practitioners in China and Thailand from 2011 to 2018 is shown in Figure 3. Journalism and communication are intimately tied to the growth of advertising education in universities and colleges in both China and Thailand. From 2011 to 2018, an average of 20.0% of advertising practitioners in China had graduate degrees, an average of 41.0% had undergraduate degrees, an average of 13.4% had specialist degrees, and an average of 25.6% had others. In Thailand, there are 13.4% more practitioners with graduate degrees than in China, 6.6 percentage points less. 29.1% of students are undergraduates on average, which is 11.9 percentage points fewer than China. The average percentage of specialized students is 30.7%, which is 17.3 percentage points more than China. Others accounted for an average of 26.8%, 1.2 percentage points more than in China. 14.5% of advertising professionals in China have improved their education at bachelor's degree and above from 2011 to 2018, compared to 17.6% in Thailand. With the development of the economy and multimedia, both China and Thailand are paying more attention to the advertising industry and subsequently investing more in advertising education, which makes the competition in the advertising industry converge to the social average.

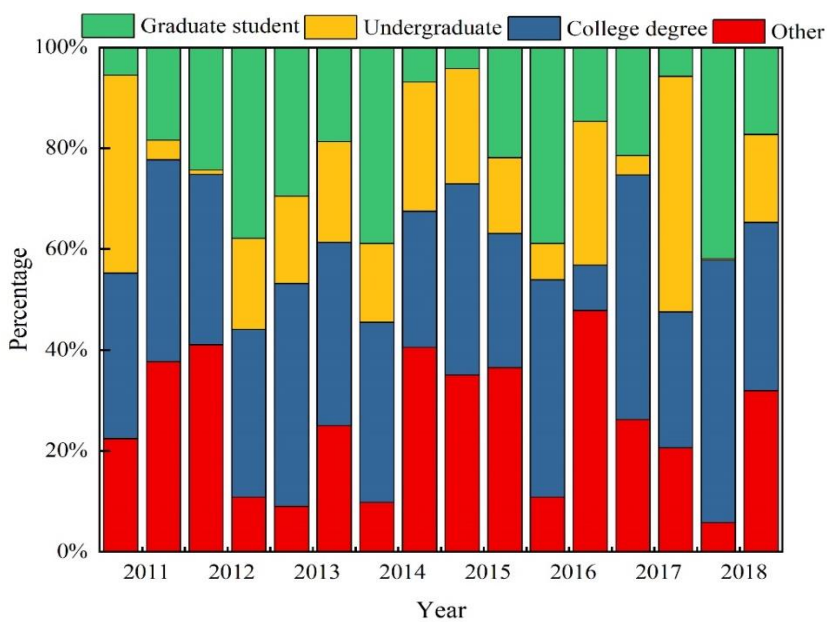

Figure 3 Comparison of the educational distribution of advertising practitioners

Volume: 8, No: 3, pp. 125-142
ISSN: 2059-6588 (Print) | ISSN 2059-6596 (Online)

KELM-based faculty analysis

The comparison of advertising education faculty strengths in Chinese and Thai universities from 2001 to 2020 is shown in Figure 4. In the 21st century, with the development of higher education in both countries, advertising education in Chinese and Thai universities has further developed. In Chinese universities, the faculty-to-student ratio of advertising education climbed from 0.011 to 0.098 between 2001 and 2020, a roughly seven-fold rise. Similarly, the teacher-student ratio of advertising education in Thai universities has increased from 0.002 to 0.078, an increase of nearly 30 times. This is both an effect of the general expansion of higher education in both countries and a shift in advertising education from industry training to academia. Among the faculty of advertising programs in Chinese universities, the percentage of professors increased from 31.0% in 2001 to 49.5% in 2020, and the percentage of associate professors increased from 6.9% to 63.7%. Correspondingly, the percentage of professors among advertising faculty in Thai universities increased from 9.0% in 2001 to 40.0% in 2020, and the percentage of associate professors increased from 1.4% to 54.6%. With the simultaneous development of both education and industry, both China and Thailand have made great strides in both academic and industrialization levels.

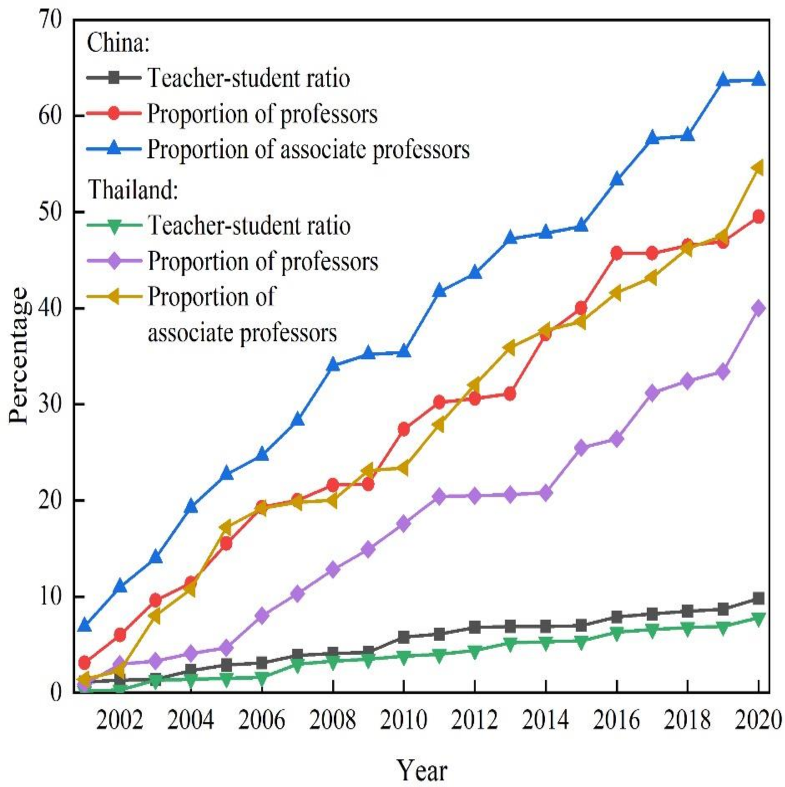

Figure 4 Comparison of teachers in advertising education in colleges and universities

Analysis of KELM-based advertising teaching evaluation

The data set is created according to the evaluation dimensions of college advertising education such as cultivation objectives, cultivation specifications, curriculum system, faculty conditions, quality assurance mechanism, etc., and mined and analyzed based on KELM algorithm, to create a thorough assessment index for college advertising instruction. Figure 5 compares the institutions in China and Thailand using a complete assessment measure of advertising teaching. From 2001 to 2016, the comprehensive evaluation index of advertising teaching in Thai universities improved from 59.84 to 73.56, with a relative increase of 22.93%. Comparatively speaking, China's comprehensive assessment index for advertising education increased from 70.81 to 84.86, a relative growth of 19.84%, which is 3.09 percentage points less than Thailand's. Combined with the previous analysis, although the academic level of advertising education in Chinese colleges and universities is significantly stronger than that in Thailand, there is no equivalent gap in teaching practice. From 2001 to 2016, the average annual growth rate of the comprehensive evaluation index of advertising teaching in Thai colleges and universities was maintained at 1.39%, while that of China was 1.21%. Entering the new media era, advertising education in both China and Thailand are facing a period of transition, but Thai universities are currently seen to be better adapted.

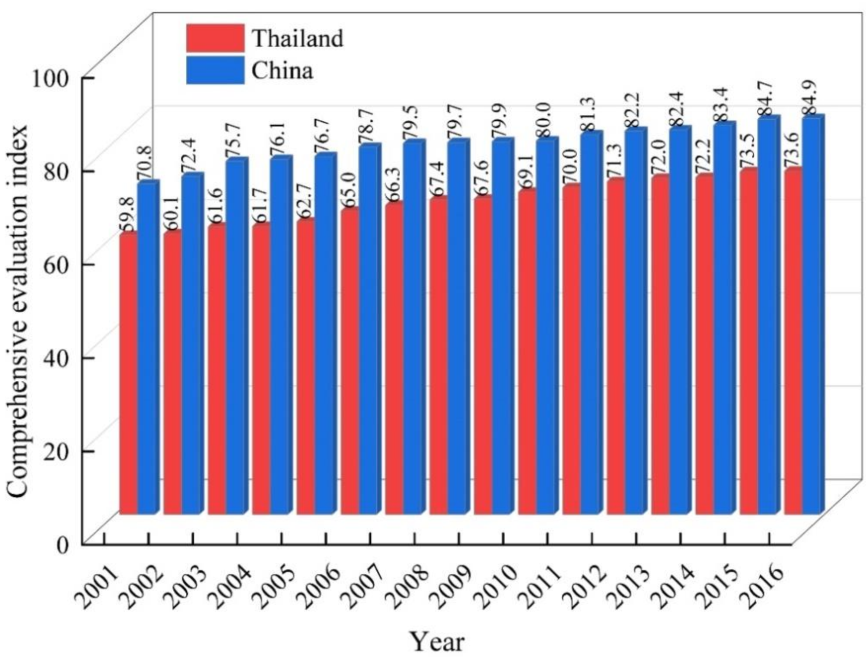

Figure 5 Comprehensive evaluation and comparison of advertising teaching

Volume: 8, No: 3, pp. 125-142
ISSN: 2059-6588 (Print) | ISSN 2059-6596 (Online)

Conclusion

Based on the extreme learning machine algorithm, this study compares and contrasts the advancement of advertising education in Chinese and Thai colleges. It also suggests the introduction of a kernel function to address the ELM algorithm's lack of generalization capability, so as to analyze the distribution of advertising practitioners' education, faculty strength and comprehensive evaluation of teaching in China and Thailand by using the KELM algorithm. The education of advertising practitioners in China in 2020 is 12% higher than that of Thailand in terms of bachelor's degree and the percentage of those with education above is 12.4% higher than that of Thailand. Moreover, the teacher-student ratio of advertising majors in universities in both countries has increased rapidly from 2001 to 2020, by about 7 times and 30 times respectively. The comparative analysis based on KELM algorithm brings the following insights for the development of advertising education in China:

(1) Establishing the concept of student as the main body

In advertising education, the distinction between the "subject" and "principal" of students and teachers can encourage both sides to actively carry out teaching activities. The theoretical underpinnings of advertising should serve as the basis for advertising education in colleges and universities, taking market feedback as the standard for testing the results of advertising education, taking market demand as the guide for setting training goals, awakening students' subjective consciousness, and giving full play to students' subjective initiative in learning.

(2) Promote the process of socialization of education

Teachers' ideology should be socialized, they should be concerned about the development of the advertising world in time, they should grasp the latest theoretical perspectives in time, and apply these new knowledge in the theoretical teaching process to ensure that students can be in close contact with the latest advertising perspectives on the premise of mastering basic professional knowledge, so that they can also join in the thinking of the development of advertising itself.

(3) Accelerate the improvement of curriculum system

The ecology of advertising education in China needs to be regulated and repaired from within advertising education itself. For the new model of advertising education, a new curriculum system is needed. The curriculum structure of advertising majors should be from basic to professional to frontier, from knowing to knowledgeable, from high precision to wide caliber, from applicability to advanced.

References

Alhabash, S. (2021). Humanizing Advertising Education: Reflection and Insights for Post-

Pandemic Pedagogy. *Journal of Advertising Education, 25*(1), 6-12.

Chang C, S. N. (2018). Teaching Reform and Practice of Undergraduate Advertising Education An investigation in Anhui University of Finance & Economics. *Journal of Educational Institute of Jilin Province*.

Fianu, E. S. (2022). Analyzing and Forecasting Multi-Commodity Prices Using Variants of Mode Decomposition-Based Extreme Learning Machine Hybridization Approach. *Forecasting, 4*(2), 538-564.

Hou J, C. D. O. (2015). On Advertising Education Abroad and the Enlightenment. *Theory and Practice of Education*.

Hwang, Y., Yum, J.-Y., & Jeong, S.-H. (2018). What components should be included in advertising literacy education? Effect of component types and the moderating role of age. *Journal of Advertising, 47*(4), 347-361.

Jing B, Q. J., University Z W. (2018). Innovation of Extracurricular Training System of Advertising Discipline Under New Media Environment. *Journal of Zhejiang Wanli University*.

Kaewkatorn, C. (2013). The relationship between personality type and learning achievement among advertising students at Assumption University of Thailand. *Scholar: Human Sciences, 5*(2), 93-93.

L, S. Y. (2019). Advertising Education at a Cross road. *Journal of Advertising Education, 23*(2), 155-163.

Liu, C. (2021). Precision algorithms in second-order fractional differential equations. *Applied Mathematics and Nonlinear Sciences, 7*(1), 155-164.

Ma, L. (2021). Realization of artificial intelligence interactive system for advertising education in the era of 5G integrated media. *Wireless Networks*, 1-14.

Morimoto, M. (2019). Advertising Education in Japan: Challenges in the Age of Globalization. *Journal of Advertising Education, 23*(2), 144-150.

Rastgou, M., Bayat, H., Mansoorizadeh, M., & Gregory, A. (2022). Estimating soil water retention curve by extreme learning machine, radial basis function, M5 tree and modified group method of data handling approaches. *Water Resources Research, 58*(4), e2021WR031059.

She S, Z. Z. (2018). Technology Logic Drives Advertising Education Transformation in China during the Mobile Internet Era: A Survey Based on Teachers of Advertising. *Advertising Panorama*.

Yan Q F, Z. L. P. (2016). Reform and Practice of Corel DRAW in Major of Advertising Design in China's Universities. *Journal of Chengdu Normal University*.

Zha C C, Y. L. I. (2016). The Curriculum System and Teachers Structure of American Universities' Advertising Education. *Journalism Bimonthly*.

Zhang Y, Z. H., Humanities S O. (2019). A Study on Advertising Education Reform Driven by New Technology. *Art and Design*.

Zhao, W., & Ji, C. (2019). Advertising discipline in higher education. *New Trends and Issues Proceedings on Humanities and Social Sciences, 4*, 8-13.