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Innovation and practice of cross-cultural marketing model driven by AI technology

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Abstract: The quality of cross-cultural marketing is related to the prospect of business development. This paper analyzes the challenges encountered by international companies in cross-cultural marketing. A two-stage feature selection algorithm based on information gain and Pearson's correlation coefficient (IG-PPMCC-PCA) is proposed to optimize sales feature dimensions in combination with principal component analysis. A causal inference-driven gain model is constructed to predict the incremental user transaction willingness under marketing intervention. The results show that the gain model in this paper performs well in dataset training, with a mean square error of 78.6460, an absolute error of 1.51%, and AUUC and Qini reaching 0.8365 and 0.1295, which are better than the other five comparison models. Under the cost constraints, the model in this paper reaches the user group bringing 8.34% more than randomly selecting users. The intelligent marketing gain model that integrates feature selection and causal inference can significantly improve the accuracy and cost-effectiveness of cross-cultural marketing decisions.

Index Terms IG-PPMCC-PCA algorithm; gain model; cross-cultural marketing; principal component analysis; causal inference

I. Introduction

The cultural market is a place for the exchange of cultural and artistic products and the provision of paid cultural service activities to the required users with the law of value as the starting point, and is a bridge between consumers and cultural and artistic products [1]. With the continuous improvement of people's quality of material and spiritual life, the traditional sales concept of single cultural products has been difficult to meet the growing cultural needs of people [2], [3]. In order to further promote the exchange of multicultural information and the development of the cultural market, the cross-cultural marketing mix model is introduced into the cultural market so as to promote the healthy and comprehensive development of the cultural market [4], [5].

Under the wave of globalization, cross-cultural marketing has become a winning strategy for international enterprises. Cross-cultural marketing can not only promote the communication and understanding between different cultures, but also help enterprises to explore new markets, expand international influence, enhance brand value and competitiveness, and lay the foundation for sustainable development of enterprises [6]-[8]. On the one hand, cross-cultural marketing can help enterprises deeply understand the cultural characteristics of the target market, consumer behavior and market environment, so as to develop more effective marketing strategies [9], [10]. On the other hand, by overcoming the barriers brought by cultural differences through cross-cultural marketing strategies, enterprises can also better communicate and interact with local consumers, so as to establish a good brand image and customer loyalty [11], [12]. However, how to cross the cultural barriers to marketing activities is a major problem faced by multinational enterprises, and whether it can be successfully solved is very important for the development of enterprises. With the development of the times, enterprises gradually tend to introduce artificial intelligence technology when formulating marketing strategies and tactics, and carry out cultural marketing according to the cultural characteristics and cultural background of the market country, so as to maximize the internationalization of the enterprise and its business objectives [13]-[15].

This paper analyzes the problems of cross-cultural marketing from two aspects: cultural differences and consumer behavior differences. The information gain and Pearson correlation coefficient are fused by the IG-PPMCC-PCA algorithm to screen high-contribution sales characteristics and realize data dimensionality reduction to reduce the computational complexity. The gain model is constructed to quantify the causal effect of marketing interventions, and the A/B test is used to generate unbiased data to support incremental prediction and accurately identify target users. The application effect of the proposed model is analyzed through performance comparison experiments and marketing effect practice.

II. Analysis of cross-cultural marketing related technology based on AI technology

In this paper, starting from the difficulties faced by international enterprises in cross-cultural marketing, the IG-PPMCC-PCA algorithm is chosen to calculate the relationship between sales characteristics and best-seller degree. It also constructs a gain model to predict the growth of users' willingness to trade under marketing activities.

II. A. Major Challenges Faced by International Enterprises in Cross-Cultural Marketing

II. A. 1) Challenges posed by cultural differences

One of the biggest challenges faced by international companies in cross-cultural marketing is cultural differences. There are significant differences in language, religion, values, customs, etc. across countries and regions, and these differences have a significant impact on marketing activities. For example, in high-context cultures, people focus on extra-verbal meaning and non-verbal communication, while in low-context cultures, people prefer direct and clear expressions. For example, in individualistic cultures, people emphasize personal interests and achievements, while in collectivistic cultures, people value collective interests and harmonious relationships. These cultural differences need to be fully considered by international enterprises in the process of marketing strategy development and implementation, otherwise it may lead to marketing errors or even cultural conflicts.

II. A. 2) Challenges posed by differences in consumer behavior

Consumers in different cultures have significant differences in their purchasing motives, decision-making styles, brand preferences, etc., which bring challenges to cross-cultural marketing by international enterprises. For example, in Eastern cultures that emphasize face, consumers may prefer luxury goods that show off their status and position, while in Western cultures that value practicality, consumers may prefer cost-effective goods. Another example is that in cultures that value individualism, consumers base their purchasing decisions more on personal preferences, while in cultures that value collectivism, consumers' purchasing behavior is more likely to be influenced by the group.

II. B. IG-PPMCC-PCA sales feature selection algorithm

Taking the cross-cultural marketing of sports shoes and apparel enterprises as an example, eight main sales characteristics are extracted from the original sales data of the best-selling products, which are: the year of the product's launch, the season to which the product belongs, the color of the product, the actual retail price of the product, the discount section to which the product belongs, whether the product is endorsed by celebrities or not, the gender of the consumers to whom the product applies, and the product series to which the product belongs.

The extracted sales features are of great theoretical significance. However, in specific application scenarios, classification models are usually more sensitive to parameters such as sample feature dimensions during training. In order to determine the optimal dimensionality of the sales data samples, a two-stage sales feature selection algorithm (IG-PPMCC-PCA) is proposed in this paper. The algorithm first proposes a feature contribution evaluation metric based on information gain and correlation coefficient to filter the original set of sales features, and then calculates the optimal dimensionality of the samples using principal component analysis (PCA).

The feature selection results output from the IG-PPMCC-PCA algorithm will be used to train the WOA-SVM best-seller classification model. The following paper describes the specific concepts of the IG-PPMCC-PCA algorithm in detail.

Information gain is defined as the difference between the conditional entropy and the information entropy, which can measure the contribution of new features to the classification problem. The concepts of self-information, information entropy, conditional entropy and information gain are introduced as follows:

1) Self-Information: The amount of information generated when a source (random event) emits a certain symbol that produces a certain definite result is called self-information. The self-information of a random variable X taking the value x_i is defined as:

$$H_p(X) = E(I_p(X = x_i)) = \sum_{i=1}^{n} p(X = x_i)\log\frac{1}{p(X = x_i)} \tag{1}$$

2) Information entropy: It is an extremely important concept in information theory, which can be used to measure the uncertainty of the values of a random variable and the complexity of a system. If all values of a discrete random variable X have the same probability, then the information entropy of X will reach the maximum value. At this point, this random variable X has the maximum amount of self-information. If some of the values of the discrete random variable X have high probability, then its information entropy will be relatively small. The formula for information entropy is as follows:

$$I(X = x_i) = \log\left(\frac{1}{p(X = x_i)}\right) \tag{2}$$

3) Conditional entropy: is defined as the mathematical expectation of the amount of self-information that is the conditional probability. Its computational expression is:

$$H(X\mid Y)=\sum_{i=1}^{N_X}\sum_{j=1}^{N_Y}p(x_i,y_i)\ln p(x_i\mid y_i) \tag{3}$$

where, the larger $H(X\mid Y)$, the larger the uncertainty of X represents the condition that Y is known, i.e., the smaller the nonlinear correlation between Y and X.

4) Information gain: is used to measure the attribute contributes information to the sample classification. The more information contributed, the more important the attribute is, so the information gain is defined as follows:

First define the information entropy of the category variable $C=\{C_1,C_2,\cdots,C_i\}$:

$$H(C)=\sum_{i=1}^{m}p(C_i)\ln\left(\frac{1}{p(C_i)}\right) \tag{4}$$

Next define the conditional information entropy of the category C conditional on the attribute variables $X=\{X_1,X_2,\cdots,X_i\}$:

$$H(C\mid X)=\sum_{i=1}^{m}\sum_{k=1}^{n}p(C_i,x_k)\ln\left(\frac{1}{p(C_i\mid x_k)}\right) \tag{5}$$

The final information gain is:

$$IG(C\mid X)=H(C)-H(C\mid X) \tag{6}$$

Since the sales features in the sales sample feature set are not independent of each other and there is some correlation between different sales features, only the information gain is used to reflect the degree of functionality of different features to the classification target. In order to measure the correlation between sales features and reduce the redundancy of the sales feature set, the PPMCC correlation coefficient is introduced in this paper. A detailed description of PPMCC is given below.

PPMCC is a commonly used statistical method to measure the strength and direction of a linear relationship between two variables. It is based on the concept of covariance and the correlation coefficient is obtained by calculating the product of the covariance of two variables divided by their respective standard deviations.

The correlation coefficient takes values ranging from -1 to 1. The principle of Pearson's correlation coefficient is shown in equation (7):

$$\rho_{X,Y}=\frac{\operatorname{cov}(X,Y)}{\sigma_X\sigma_Y}=\frac{\sum_{i=1}^{n}\left(X_i-\bar{X}\right)\left(Y_i-\bar{Y}\right)}{\sqrt{\sum_{i=1}^{n}\left(X_i-\bar{X}\right)^2}\sqrt{\sum_{i=1}^{n}\left(Y_i-\bar{Y}\right)^2}} \tag{7}$$

In Eq. σ_X and σ_Y are the sample variances of X and Y, respectively. $\operatorname{cov}(X,Y)$ denotes the covariance of X and Y. $\bar{X}$, $\bar{Y}$ denotes the sample mean. $\rho_{X,Y}$ denotes the correlation coefficient. The closer the absolute value of $\rho_{X,Y}$ converges to 1, the stronger the linear relationship between the two variables. The closer the absolute value of $\rho_{X,Y}$ is to 0, the weaker the linear relationship between the two variables.

When it is positive, it means that there is a positive correlation between the two variables. When it is negative, it means that there is a negative correlation between the two variables. In short, the larger the calculation result, the better the feature selection.

$$y(x)=\frac{1}{\sqrt{2\pi}}\int_{-\infty}^{x}e^{\left(\frac{t^2}{2}\right)}dt \tag{8}$$

$$d(f_i,g)=y\left(IG(f_i)+PPMCC^2(f_i,g)\right) \tag{9}$$

where Equation (8) gives a method of normalizing the data based on the probability density function of the standard normal distribution, with $y(x)$ taking values between 0 and 1. Equation (9) gives the specific calculation method of feature selection index in this paper. f_i is the feature in the sales feature set, and $IG(f_i)$ is the information gain of f_i. $PPMCC(f_i,g)$ is the correlation coefficient between the sales feature f_i and the objective function of the best-seller degree g.

In order to simplify the analysis of feature contribution, this paper does not consider the direction of the correlation between the sales feature f_i and the objective function of best-seller degree g. Therefore, Equation (9) takes the sum of the square of the PPMCC and the information gain as the contribution of the sales feature f_i to the bestseller degree objective function g, and normalizes the contribution to between 0 and 1.

There are a large number of methods to calculate the optimal dimensionality of the PCA dimensionality reduction algorithm, and in this paper, the accuracy of the classification model under the dimensionality reduction sample set is used as the fitness function. In this case, the maximum point of the fitness function is the optimal dimension of the sample.

II. C.Definition of gain modeling

The incremental model (UM) is a methodology for assessing the additional gains resulting from a given intervention. The model is mainly applied to predict the increase in users' willingness to transact facilitated by cross-cultural marketing campaigns, the so-called incremental (U), and to identify those users who may be genuinely affected by the marketing campaigns. Thus, the gain model is considered an important tool for realizing smart marketing.

The model is defined as follows: assuming that there are N users, for each of them i, $Y_i(1)$ represents the result obtained after implementing marketing intervention on the user, for example, triggering a marketing action on user i, the result is that the user completes the order; and $Y_i(0)$ represents the result obtained without intervening on the user, for example, not triggering a marketing action on user i, the result is that the user completes placing an order. The causal effect (CE) of user i is calculated as follows (10):

$$\tau_i = Y_i(1) - Y_i(0) \tag{10}$$

The goal of the gain model, on the other hand, is to maximize increment τ_i, which captures the improvement effect of taking a marketing intervention compared to not taking any marketing intervention, i.e., it is defined by comparing the difference in outcomes before and after the implementation of the marketing intervention. Therefore, in order to quantify the overall effect of implementing a marketing intervention for all users, the concept of Conditional Average Causal Effect (CATE) is proposed. CATE quantifies the intervention effect by estimating the expected value of the causal effect for all users, which is calculated as follows (11):

$$CATE : \tau(X_i) = E\left[Y_i(1) | \ X_i\right] - E\left[Y_i(0) | \ X_i\right] \tag{11}$$

Equation (11) above demonstrates the ideal form of incremental computation, where X_i represents the set of features of user i, indicating that the intervention conditions in the causal effect are based on user features.

In practice, however, it is not possible to observe the outputs of user i in the two different cases of marketing intervention and no marketing intervention at the same time, i.e., $Y_i(1)$ and $Y_i(0)$ are usually not available at the same time. Therefore, a binary variable $W_i k_3$ is introduced to indicate whether or not a marketing intervention is implemented for user . If marketing is implemented, W_i is equal to 1; if it is not implemented, W_i is equal to 0. At this point, the output that user h_4 can actually be observed is denoted as , and is calculated as shown in equation (12) below:

$$Y_i^{obs} = W_i Y_i(1) + (1 - W_i) Y_i(0) \tag{12}$$

Under the Conditional Independence Assumption (CIA), which assumes that marketing intervention strategies and user characteristics are independent of each other, the calculation of $\tau(X_i)$ can be written as Equation (13) below and the CIA can be expressed as Equation (14) below:

$$\tau(X_i) = E\left[Y_i^{obs} \middle| X_i = x, W_i = 1\right] - E\left[Y_i^{obs} \middle| X_i = x, W_i = 0\right] \tag{13}$$

$$CIA : \{Y_i(1), Y_i(0)\} \perp W_i \middle| X_i \tag{14}$$

The increment τ_i serves as a quantification of the effectiveness of the gain model, with larger values indicating better model effectiveness. Direct optimization of the increment is difficult to perform because a single user cannot generate experiences in both marketing intervention and non-marketing intervention states at the same time. However, random assignment of user traffic through A/B testing allows for the formation of two separate groups: one group receives the marketing intervention and the other does not. Such an experimental design ensures consistency in the distribution of characteristics between the two groups of users, thus making user characteristics and cross-cultural marketing interventions independent of each other. By comparing the experimental results of the two groups of users, a single user increment can be modeled. Therefore, in practice, A/B randomized experiments are a crucial step in the process of constructing the model, which provides unbiased sample data for the model and thus ensures the validity of the increment τ_i.

Incremental modeling incorporates the dual properties of causal inference and machine learning. It is first and foremost a causal inference problem because performance in cross-cultural marketing intervention and non-cross-cultural marketing intervention states cannot be observed simultaneously at the individual level. To address this challenge, the gain model employs a randomized A/B testing approach, where users are randomly assigned to experimental and control groups, thus enabling accurate estimation of causal effects. In addition, the construction of the gain model is also a machine learning process that involves completing multiple model training and comprehensively screening the optimal model through multi-dimensional performance evaluation metrics to accurately predict the gain.

III. Cross-cultural marketing practices based on gain modeling

In this chapter, correlation analysis and principal component extraction are performed on the selected sales features, after which the sales gain model is constructed. The marketing capability of the model is analyzed through performance comparison and practical application.

III. A. Sales characterization

III. A. 1) Overview of the statistical characteristics of the data

As an example, the sales data of the No. 1 store of a large sports shoes and apparel multinational company in City A is used to count the sales data corresponding to each hot-selling item, including the maximum value, minimum value, average value, median, quartile, and other information. Table 1 shows an overview of the sales data information of Store No. 1. From the comparison of the mean, median and quartile of the data in the table, it can be seen that the sales distribution of sports shoes and apparel items is more concentrated under specific temperatures, prices and other circumstances. This means that in terms of the season, the actual retail price, and the discount segment, Store No. 1 in City A has the relevant data to meet the sales characteristics of hot products and meets the requirements of the analysis.

Table 1: An overview of the sales data information of Store No. 1

Index	Maximum value	Minimum value	Mean value	Median	Quartile
Weekly_Sales	55591	14327	46103	18523	22251
Temperature	94.63	31.43	61.30	63.31	90.42
Price	3.606	2.512	3.231	3.195	3.696
MarkDown1	34277.4	420.0	8390.5	6144.2	9297.7
MarkDown2	41011.3	0.54	2961.37	142.84	1147.41
MarkDown3	53805.6	0.25	1255.43	21.97	86.70
MarkDown4	36403.7	8.1	3716.2	1622.4	3395.3
MarkDown5	21475.6	574.2	5038.5	4125.0	5185.5

III. A. 2) Feature correlation analysis

Spearman correlation coefficient is used to describe the degree and direction of association between two characteristics. Spearman correlation analysis was performed for the eight categories of sales characteristics to which each data belongs. Figure 1 shows the results of the correlation analysis of each sales characteristic. In the figure, 1-8 represent the year of product launch, the season of product, the color of product, the actual retail price of product, the discount section of product, whether the product is endorsed by celebrities or not, the gender of applicable consumers, and the series of product, respectively. The correlation coefficients of the eight sales features are all between 0.1 and 0.3, not exceeding 0.5, from which it can be judged that there is no significant correlation between the extracted sales features, and the next step of principal component analysis can be carried out.

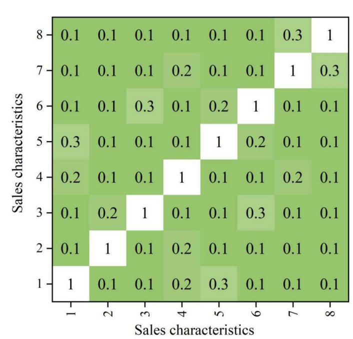


Figure 1: Analysis results of the correlation of sales characteristics

III. A. 3) Principal component analysis

The matrix of regression coefficients was derived from the characteristic data of all hot-selling products in Store One in time series and was downscaled using principal component analysis. The cumulative contribution ratio was determined to be 0.9. Table 2 shows the number of principal components and the corresponding cumulative contribution ratio, standard deviation, and proportion of variance after calculation. The cumulative contribution rate of the first five sales features reaches 0.9155, which is more than 0.9, so the number of principal components is determined to be 5, which are the year of product launch, the season to which the product belongs, the color of the product, the actual retail price of the product, and the discount segment to which the product belongs. Replacing the original 8 feature variables with these 5 principal components reduces the computational difficulty and improves the marketing program prediction.

Table 2: Principal component analysis results

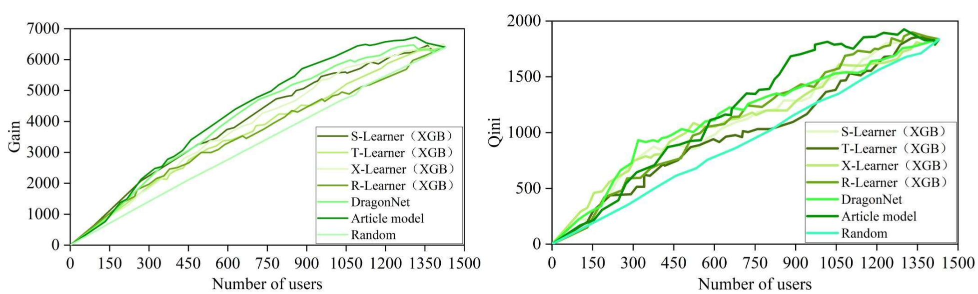
Number of principal components	Standard deviation	Variance ratio	Cumulative contribution rate
1	2.0528	0.2257	0.2257
2	1.9020	0.2034	0.4291
3	1.7285	0.1857	0.6148
4	1.6378	0.1776	0.7924
5	1.1027	0.1231	0.9155
6	0.4809	0.0457	0.9612
7	0.3371	0.0319	0.9931
8	0.1702	0.0069	1.0000

III. B. Gain model performance comparison

Due to the small amount of store-specific sales data used in the previous section, which cannot fully reflect the performance effect of the gain model, a large benchmark test dataset, the IHDP dataset, is selected as the dataset for the validation of the causal inference performance of the gain model in this section.The IHDP dataset is produced based on real data, and adopts a randomized control experimental design. The marketing intervention was used as the intervening variable, and the user's willingness to transact was used as the target variable. 75% from the dataset was randomly selected as the training set and the remaining 25% as the test set, the practice data was used to fit the model and the test data was used for prediction.

Comparing the area under the elasticity curve (AUUC value) and the size of the Gini coefficient (Qini coefficient) of the same type of marketing gain models S-Learner (XGB), T-Learner (XGB), X-Learner (XGB), R-Learner (XGB), the deep learning-based DragonNet model, and the model of the present paper, we estimate the causal effect benefits of the model's marketing programs on marketing revenue. Larger AUUC values and Qini coefficients indicate better performance of the model.

Figure 2 shows the comparison of cumulative gain curves and Gini curves under each gain model. Table 3 shows the comparison of evaluation metrics for the IHDP data test set. The gain model in this paper is always above the other models in the range of 1600 user volume, and the Gini curve shows a steady upward trend, obtaining the optimal marketing benefits after the user volume exceeds 700. Further comparison reveals that the mean square error of this paper's model is only 71.6460, and the absolute error is only 1.01%, meanwhile, the AUUC and Qini are the largest, reaching 0.8565 and 0.1395. In several comparison indexes, this paper's model obtains the optimal results, which indicates that this paper's model has a better prediction performance of marketing effectiveness compared with other gain models of the same type.



(a) Gain (b) Gini

Figure 2: Comparison of Gain and Gini coefficient under each gain model

Table 3: Comparison of evaluation indicators in the IHDP data test set

	ATE	Mean square error	Absolute error	AUUC	Qini
True value	4.5197	0	0	-	-
S Learner (XGB)	4.3205	86.7341	7.31%	0.7187	0.1063
TLearner (XGB)	4.4271	83.1555	2.85%	0.7423	0.0877
X Learner (XGB)	4.2200	86.9052	6.12%	0.7222	0.1032
R Learner (XGB)	4.1113	81.4564	3.26%	0.7360	0.1127
DragonNet	4.4752	83.4925	3.17%	0.7228	0.1013
Article model	4.4886	71.6460	1.01%	0.8565	0.1395

III. C. Effectiveness of Intelligent Marketing under Cost Constraints

The essence of building a marketing gain model is the desire to use the model to solve intelligent marketing problems. In an actual cross-cultural marketing scenario, this paper focuses on: how to select a target group for marketing reach to maximize the gain, given the limited cost? How much revenue can be generated by doing so? In this section, the trained marketing gain model will be applied to a total of 1,600 users in the test set to further explore how to maximize the gain under limited cost.

In a cross-cultural marketing campaign, if the cost of single person marketing is 2.0 yuan per person and the budget of the campaign is 3,000 yuan, this means we can only choose 1,500 users to reach. Figure 3 is the result of marketing campaign gain variation calculated based on the gain model of this paper. It can be seen that under the limitation of the cost budget, if we choose the marketing sensitive people predicted by the model and accurately reach the top 1500 user groups ranked by the gain value, it will bring 83.34% gain; while if we randomly choose the users to be reached, we can only get 75.00% gain. In other words, in the case of the same marketing cost, the precise group of people selected based on the gain model in this paper can increase the gain by an additional 8.34%, mobilizing more users' desire to purchase goods.

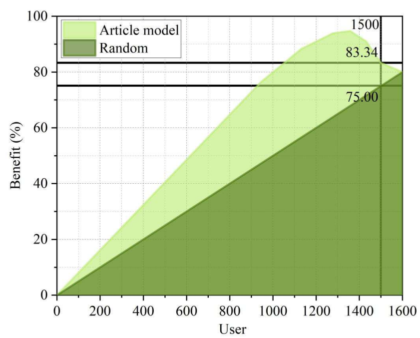


Figure 3: Gain of marketing activities calculated based on the artical model

IV. Conclusion

In this paper, we design an intelligent marketing gain model that integrates feature selection and causal inference to improve the quality of cross-cultural marketing.The IG-PPMCC-PCA algorithm compresses the sales features from 8 to 5 to reduce the computational requirements. The gain model has a mean square error of 78.6460 and an absolute error of 1.51% on the IHDP dataset, and the AUUC and Qini reach 0.8365 and 0.1295, possessing better performance than the same type of gain model. Under the cost constraint, an additional 8.34% gain is obtained over the random strategy, which can accurately reach the target users. In the future, the semantic understanding of cross-cultural scenarios can be enhanced by combining multimodal data to further improve the model's ability to reach target marketing users.

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