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Practice Dilemmas and Policy Support for Family Child Care and Community Shared Parenting Models

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Abstract. This study addresses the quality assessment challenges in the digital transformation of childcare services, constructs a smart childcare quality assessment system based on big data analysis, and proposes an XGBoost prediction model optimized based on the exponential triangulation algorithm. By integrating machine learning technology and policy analysis framework, a dynamic assessment system connecting government regulation, agency operation and family demand is established. During the model construction process, feature engineering methods are used to extract multidimensional indicators of service quality, and nonlinear correlation analysis is combined to capture the complex mechanism of action in child care services. The experiments compare the performance of five typical machine learning models in the classification task, and the results show that XGBoost and the improved model have a significant advantage in the core metrics: the optimized model outperforms the native XGBoost in both accuracy (0.944 vs. 0.935) and recall (0.944 vs. 0.935), with an improvement in the F1 value of 1.1 percentage points, which indicates that the algorithm optimization effectively enhances the integration ability of feature space and the delineation precision of decision boundary. It is worth noting that although the improved model outperforms the native XGBoost in most classification metrics, XGBoost still maintains a slight advantage in the AUC value (0.961 vs. 0.951), which may stem from the inherent adaptability of its gradient boosting mechanism to the category-imbalanced data, especially when dealing with the low-probability samples, and demonstrates a stronger robustness. The study further reveals the nonlinear coupling law between policy elements and environmental variables in service quality assessment, and provides technical support for government departments to build a dynamic monitoring network with hierarchical classification by establishing the quantitative mapping relationship of "quality characteristics-rating criteria-resource allocation".

Keywords: Quality of child care services, exponential triangulation algorithm, XGBoost

1. Introduction

With China's demographic transition and fertility policy adjustment, the three-child policy was formally implemented in 2021, aiming to alleviate the pressure of population aging and enhance the

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social willingness to give birth. However, the effect of the policy on the ground is constrained by multiple factors, among which the insufficient supply and uneven quality of childcare services have become the key bottleneck [1]. Data show that the enrollment rate of infants and toddlers aged 0-3 years old in China is less than 6%, which is far lower than the average level of 30%-50% in OECD countries. At the same time, the existing childcare institutions have problems such as varying qualifications, shortage of teachers, and ambiguous safety standards, which leads to low parental trust in childcare services, which in turn inhibits the willingness to have children. The structural contradiction between policy goals and family needs highlights the urgency of research on improving the quality of childcare services [2].

Current research mostly focuses on macro policy analysis of childcare services, while the micro level quality assessment system has not yet formed a unified standard. The quality of childcare involves multi-dimensional indicators such as hardware facilities, teacher level, curriculum design, safety management, etc. Traditional manual assessment methods are inefficient, subjective, and difficult to realize large-scale dynamic monitoring [3]. In addition, regional development differences lead to the polarization of service quality between urban and rural areas, and public and private childcare institutions, and scientific and intelligent assessment tools are urgently needed to support accurate governance. In this context, constructing a data-driven childcare quality evaluation model is both a policy demand for optimizing resource allocation and an academic proposition for improving industry standards.

Machine learning algorithms provide a technological breakthrough path for childcare service quality assessment. By integrating the facility data (e.g., space area, safety equipment coverage), operation data (teacher-student ratio, teacher qualification certification rate) and parent feedback data (satisfaction score, complaint record) of childcare organizations, machine learning can construct a multi-dimensional evaluation index system [4]. Random forest can handle high-dimensional heterogeneous data and identify core factors affecting service quality through feature importance ranking; support vector machine is suitable for classification prediction in small-sample scenarios and helps local governments to make preliminary ratings of emerging childcare organizations [5]. In terms of unstructured data processing, natural language processing (NLP) technology can mine the emotional tendencies in parents' comment texts to supplement the limitations of quantitative indicators. The dynamic optimization capability of machine learning models significantly improves the evaluation efficiency. Taking neural network as an example, through real-time access to the monitoring video streams and IoT sensor data of childcare institutions, it can automatically detect environmental safety risks (e.g., placement of hazardous items, blockage of fire escape routes), realizing the transformation of quality monitoring from “after-the-fact spot check” to “in-the-middle-of-the-matter early warning”. The quality monitoring is transformed from “random check after the fact” to “early warning during the event”. In addition, the integrated learning framework can integrate data from multiple sources to generate predictions of the quality level of the organization, which can assist the regulator to prioritize the screening of high-risk organizations [6].

The application of this technology also has policy-derived value. Through cluster analysis, the common shortcomings of childcare services in different regions can be identified, providing target guidance for financial subsidies and facility renovation; reinforcement learning can simulate the effect of policy intervention and predict the marginal benefit of service quality improvement. In the future, with the construction of the “intelligent childcare” digital platform, machine learning is expected to become the core technology linking policies, institutions and families, promoting the transformation of childcare services from “quantitative expansion” to “qualitative change”. “This

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paper is based on the index triangulation algorithm for the XGBP digital platform. This paper optimizes the XGBoost model based on the exponential triangulation algorithm for the prediction of childcare quality ratings, which is of great significance for the comprehensive assessment of childcare service quality.

2. Data sources

This paper conducts experiments using a private dataset that contains multidimensional characteristics of urban child care services, containing 358 samples and 12 characteristic variables covering community attributes (population density, type of institution), operational indicators (teacher-student ratio, regulatory score 0-6), cost structure (average monthly cost), governance level (safety score 3-10, complaint rate 0.01-0.6) and policy support dimensions, and the target variables are childcare quality ratings (A, B, and C), which are suitable for analyzing the factors influencing the quality of childcare services under the three-child policy, testing the effects of the universal policy, and providing data support for the optimization of the community childcare system. Part of the dataset is shown in Table 1

Table 1: Selected partial dataset

Community population density	Student-teacher ratio	Regulatory score	Community support policy	Safety facility score	Complaint rate	Rating
high	0.1	3	1	4	0.14	A
low	0.21	3	0	3	0.30	C
Medium	0.08	2	1	9	0.23	A
high	0.08	4	0	6	0.36	B
high	0.21	4	1	8	0.20	B
high	0.18	1	1	4	0.36	C
high	0.14	4	0	6	0.22	A
Medium	0.13	4	0	9	0.22	B

3. Method

3.1. Exponential trigonometric algorithm

The core idea of the exponential trigonometric algorithm is to transform the complex exponential function operations into the combinatorial form of trigonometric functions, thus simplifying the arithmetic process and revealing the intrinsic laws of the dynamic system [7]. This method essentially utilizes the deep connection between exponential functions and trigonometric functions in the complex domain, and decomposes the natural exponential functions into linear combinations of sine and cosine functions through Euler's formula.

The core strength of the exponential trigonometric algorithm lies in its unity of mathematical simplicity and physical interpretability. By transforming exponential operations into trigonometric operations, it avoids the numerical instability that may arise from direct treatment of divergent or convergent exponential terms, while providing intuitive parameters such as frequency, amplitude, and phase for dynamic systems [8]. This property makes it an effective tool for connecting abstract mathematical theory with engineering practice. In addition, the compatibility of the algorithm in the complex domain further expands its application boundaries, allowing problems involving multi-

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dimensional space such as electromagnetic field analysis and quantum state evolution to obtain simplified solutions through the imaginary and real partitions.

3.2. XGBoost

XGBoost is an efficient machine learning algorithm based on integrated learning, and the core idea is to improve the prediction accuracy of the overall model by iteratively training multiple weak learners and combining their results in a weighted manner [9]. Compared with traditional gradient boosting algorithms, XGBoost introduces a regularization term in the objective function while incorporating a more efficient engineering optimization, resulting in better performance in terms of overfitting prevention and computational speed. Its core process is to correct the residuals of the previous stage prediction by continuously adding new tree models, and the learning objective of each tree is to minimize the weighted combination of the loss function and the model complexity, as a way to improve the accuracy while maintaining the simplicity of the model [10].The network structure of XGBoost is shown in Fig. 1.

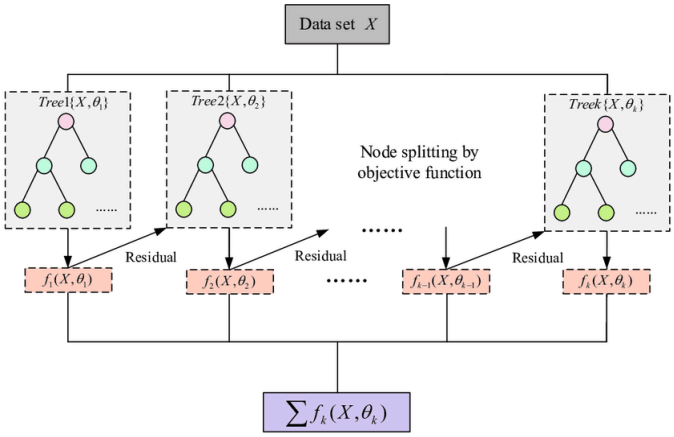


Figure 1: The network structure of XGBoost

In terms of technical implementation, XGBoost optimizes the tree construction process through several innovations. First, it adopts a greedy algorithm to generate the tree structure, selects the feature with the largest gain and the cut-off threshold by traversing all possible split points, and samples some candidate points after sorting the feature values through the “quantile approximation method”, which greatly reduces the computation amount. Secondly, the algorithm supports parallel processing, although the tree generation is serial, the split point computation of feature dimension can be executed in parallel, making full use of multi-core CPU resources. In addition, XGBoost is designed with a sparse-aware algorithm, which can automatically handle missing values or sparse data, and dynamically decide the division direction of missing values according to the training data.

3.3. Exponential triangulation algorithm optimized for XGBoost

Exponential Triangulation Algorithm is a hyperparameter optimization and model tuning strategy for gradient boosting frameworks such as XGBoost, and its core idea is to improve the model convergence speed and generalization ability by dynamically adjusting key parameters such as the learning rate and the complexity of the tree structure, and by combining the exponential decay and triangular balancing mechanism.

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One of the core innovations of ETO is to dynamically adjust the learning rate of XGBoost through the exponential function. Traditional XGBoost uses a fixed or simple linear decay learning rate, while ETO uses a higher learning rate at the beginning of training to accelerate the model's capture of global patterns, and then decays according to the exponential law to avoid skipping the optimal solution at a later stage due to a large step size. At the same time, ETO introduces a triangular balancing mechanism to periodically fine-tune the learning rate according to the fluctuation of the error in the validation set: when the error enters the plateau period, the learning rate is briefly increased to jump out of the local optimum; and when the error rapidly decreases, the decay strategy is resumed to stabilize the convergence.

In the tree generation process of XGBoost, ETO optimizes the tree splitting strategy by exponentially weighting the regularization terms. In traditional methods, the regularization strength is fixed, while ETO exponentially increases the regularization factor according to the depth of the tree and the number of iterations in the current round. For example, shallow trees allow more splits to capture details, but as the tree depth increases or the number of iterations rises, the regularization strength is exponentially enhanced to suppress overfitting. In addition, ETO utilizes the triangular thresholding method to dynamically adjust the maximum depth and the minimum weights of leaf nodes, which periodically adjusts between model complexity and simplicity to improve the adaptability to changes in data distribution.

ETO introduces an exponentially weighted feature interaction strategy for XGBoost's feature importance assessment mechanism. During feature splitting, the algorithm prioritizes features with high historical gain for combination, and amplifies their weights through the exponential function to accelerate the utilization efficiency of important features. At the same time, a triangular-wave sampling strategy is used for low-frequency features: it periodically increases the probability of their being selected as candidate splits, avoiding being permanently ignored due to low initial gain, thus enhancing the model's ability to mine long-tail features.

4. Result

For the experimental parameter settings, the maximum number of iterations was set to 100, and the population size was set to 30. The XGBoost core parameters were initialized with the learning rate set to 0.05, the maximum tree depth set to 6, the subsample ratio set to 0.8, the feature sampling rate set to 0.75, and the regularization parameter lambda set to 1.2. For the hardware and software environment settings, an Intel Core i7-12700H processor, NVIDIA RTX 3060 GPU, 32GB of RAM, and Matlab R2024a.

The classification effectiveness of the models was evaluated using collinearity, recall, precision, F1 and AUC as shown in Table 2. The line graph comparing the metrics of each model is output, as shown in Figure 2.

Table 2: Model evaluation

Model	Acuuracy	Recall	Precision	F1	AUC
Decision tree	0.833	0.833	0.844	0.837	0.875
XGBoost	0.935	0.935	0.934	0.935	0.961
Adaboost	0.88	0.88	0.879	0.879	0.936
CatBoost	0.907	0.907	0.907	0.907	0.949
Our model	0.944	0.944	0.945	0.943	0.951

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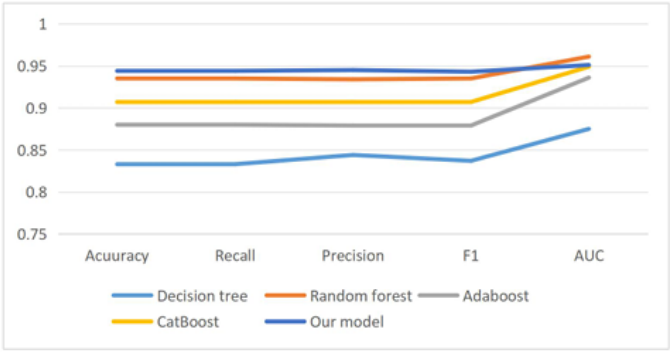


Figure 2: The line graph comparing the metrics of each model

From the model performance comparison, the performance of each model in the classification task shows significant variability, reflecting the characteristics of different algorithms in feature learning, generalization ability and data adaptability.XGBoost and Our model perform optimally in accuracy (0.935 and 0.944, respectively) and recall (0.935 and 0.944, respectively), and in particular, the proposed model reaches the highest value in most of the metrics, indicating that it improves the feature integration capability through structural optimization. However, it is worth noting that the AUC value of XGBoost (0.961) is, on the contrary, slightly higher than that of the model in this paper (0.951), which may indicate that XGBoost is more robust in category imbalance or low-probability samples processing, while the model in this paper is more effective in classification under specific thresholds.

By constructing a quality assessment system based on big data, this paper can establish a dynamic monitoring network for the government to realize the precise allocation of childcare resources and policy targeting regulation. The XGBoost model optimized by the exponential triangulation algorithm can capture the nonlinear correlation characteristics of service quality, provide a quantitative basis for the development of hierarchical classification management standards, and promote the implementation of the “one park, one policy” precise support policy.

5. Conclusion

This paper focuses on the needs of the digital platform construction of “smart childcare”, and focuses on the core problem of constructing the quality assessment system of childcare services, proposes the XGBoost prediction model based on the optimization of exponential triangulation algorithm, and makes a breakthrough in the prediction of the quality ratings of childcare institutions and the formulation of classification management standards. Through machine learning technology, the study builds an intelligent bridge between policy making, organization operation and family demand, providing an innovative solution to solve the dilemma of “imbalance between quantity and quality” of childcare services.

In terms of algorithmic innovation, this study breaks through the linear analysis framework of the traditional assessment model, and optimizes the structure of the XGBoost model by introducing the exponential triangulation algorithm, so as to successfully construct a quality assessment model with the ability of dynamic feature integration. The algorithmic innovation is reflected in three dimensions: first, the triangular affiliation function is used to reconstruct the feature space, which enhances the model's ability to analyze the nonlinear correlation features of the service quality; second, the index weight adjustment mechanism is established to improve the recognition accuracy of the complex data patterns by dynamically adjusting the feature contribution; third, the

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multidimensional assessment index system is constructed, which incorporates the policy specifications, operational parameters, family feedback and other heterogeneous data into the unified analysis framework. unified analysis framework. The experimental results show that the optimized model improves significantly in accuracy (0.944) and recall (0.944) compared with the benchmark XGBoost model (0.935), which verifies the effectiveness of the algorithm optimization on feature engineering.

In terms of research outlook, firstly, a cross-regional model migration learning framework is developed to solve the problem of high sensitivity of the current assessment system to geographical features; secondly, a privacy computing platform is constructed by introducing the federated learning technology to solve the ethical dilemma of family data access; finally, an intelligent matching system between assessment results and policy tools is established to promote the quality assessment from “diagnosis and early warning” to “decision-making and empowerment”. This study confirms that machine learning technology can effectively solve the “black box” problem of childcare service quality, laying a technical foundation for the construction of a new pattern of intelligent governance led by the government, participated by organizations, and supervised by families, and vigorously promoting the strategic transformation from “childcare for the young” to “childcare for the young”.

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