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Research on AI-Driven Advertising Optimization and Automated Decision System

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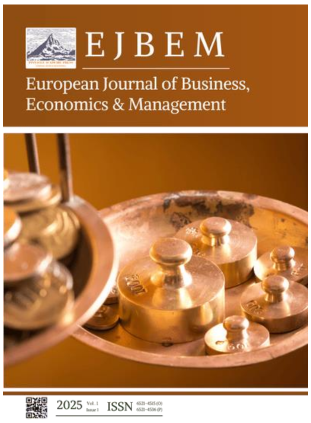

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Abstract: This paper conducts an in-depth exploration of the introduction of artificial intelligence technology in the advertising placement process. Centered on the user behavior pattern constructed with deep learning as the core and the process-based advertising decision-making applying reinforcement learning, an artificial intelligence-driven advertising placement system is constructed, including functions such as data collection and processing, model training and optimization, automated decision-making, and automatic placement control. After practical verification, it can significantly enhance the intelligence of advertising placement and the efficiency of resource allocation, and has promising application prospects and significant social value.

Keywords: artificial intelligence; advertising placement; deep learning; reinforcement learning; automated decision-making

1. Introduction

With the rapid development of intelligent marketing, advertising placement is becoming increasingly high-frequency, diversified and scenario-based. The rigid strategy of relying solely on manual experience has become difficult to adjust and precisely match with the real-time, diverse advertising demands. The emergence of deep learning and reinforcement learning has provided solutions for intelligent advertising placement. The AI-based automatic decision support system can build user profiles, implement real-time strategy optimization, placement management and control, thereby enhancing advertising effectiveness and placement efficiency.

2. The Theoretical Basis of Artificial Intelligence in Advertising Placement

2.1. User Behavior Modeling Technology Based on Deep Learning

Constructing online user behavior patterns through digital advertising channels is a prerequisite for precise delivery, mainly based on predicting the response probability of customers to activities based on their past behaviors and current conditions. The rise of deep learning has led to the gradual replacement of traditional linear structures by multi-level neural networks [1]. With deep learning, nonlinear activation functions and multi-layer structures can be used to automatically extract the relationships between high-level features and accurately obtain consumers' preferences. Given vector x of user and context features, the model for predicting click-through rate (CTR) can be expressed as:

$$\hat{y} = \sigma(W_2 \cdot \mathrm{ReLU}(W_1 \cdot x + b_1) + b_2) \quad (1)$$

Among them, W_1, W_2 is the weight matrix, b_1, b_2 is the bias term, $ReLU$ is the activation function, and σ represents the Sigmoid function, which is used to output the click probability. The accuracy of the model prediction is improved by the cross-entropy loss of the minimum predicted value $\hat{y}$ and the actual clicked label. This is a modeling method currently adopted by the CTR prediction section of mainstream advertising platforms, and it lays the foundation for the next step of placement optimization and revenue optimization.

2.2. Application Mechanism of Reinforcement Learning in Advertising Decision-Making

During the advertising placement process, real-time strategy adjustments need to be made based on dynamic factors such as user behavior and the context environment. Traditional rules are difficult to adapt to the complex and changing placement scenarios. Reinforcement learning (RL) learns the optimal placement strategy to maximize long-term benefits through continuous interaction with the environment [2]. Advertising decisions can be modeled as a Markov decision process (MDP), where state s represents the current user and environment characteristics, action a represents the advertising selection or bidding strategy, and reward r represents user feedback (such as clicks, conversions). The goal of reinforcement learning is to learn a strategy $\pi(a|s)$ so that the expected cumulative benefit is maximized:

$$J(\pi) = E_{\pi}[\sum_{t=0}^{\infty} \gamma^t r_t] \quad (2)$$

Among them, $\gamma \in [0,1]$ is the discount factor, which is used to balance short-term and long-term returns. This approach enables automatic decision-making for advertising placement, greatly enhancing the advantages of advertising placement in terms of dynamic response and ROI.

3. Design of Ai-Based Advertising Placement Optimization and Automated Decision-Making System

3.1. Overall System Architecture Design

The modular structure realizes the big data mode + model control of advertising placement. "Model-driven decisions and pattern-driven execution" is the design principle of this system. The overall process of the system is shown in Figure 1:

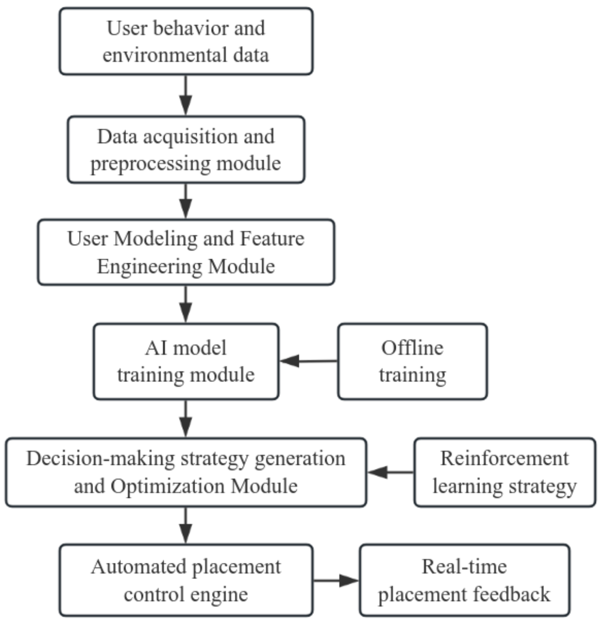

Figure 1. Flowchart of the Overall Architecture of the AI-Based Advertising Placement Optimization System.

During the operation of this system, user behavior and background data of the field environment are collected in real time from various places (such as advertising platforms, device users, etc.) first. They are cleaned and filtered through the data capture and preprocessing module, converted into structured data, and then passed to modules responsible for user profiling and feature engineering. The deep learning method is used to obtain the characteristics of user preferences and their field environment features, and form vectors with ultra-high density and high dimensionality as the materials for subsequent model training [3].

A model is trained for predicting CTR/CVR from historical behavioral data and is integrated with reinforcement learning techniques to dynamically adjust the optimal strategy. All the training models are deployed under the same inference service framework for consistency and efficiency, enabling real-time prediction and rapid response. The strategy optimization module, based on model outputs and factors such as revenue and budget, generates the final pricing, ranking, and bidding strategies to improve advertising performance.

Finally, the automatic placement manager actually releases advertisements according to the strategy instructions, and collects the feedback information of the release (such as clicks, conversions, etc.) back to form a cyclic feedback to correct the learning of the model and optimize the strategy. All the above-mentioned system components work in coordination to achieve intelligent closed-loop control at each stage from detection to prediction, decision-making and execution [4].

3.2. Design of Data Acquisition and Processing Module

The data collection and preprocessing module forms the foundation of the advertising AI system. It is responsible for completing a series of tasks such as capturing, processing, and generating training samples of various massive feature data. The operation logs such as exposure and click from the user device are obtained by the log collection system (such as Flume, Kafka), and the source data is preprocessed by the Streaming platform (such as Flink, Spark Streaming, etc.) for preliminary data transformation, deduplication, outlier discovery, etc. The results after data processing enter the feature processing stage. The transformation and embedding of categorical and numerical features are performed to generate sequential inputs, which are then used to form training samples based on the event lifecycle. The labels calibrated by timestamps are saved to HDFS or the feature pool for subsequent model training and the online inference engine. The flowchart of the data acquisition and processing module is shown in Figure 2:

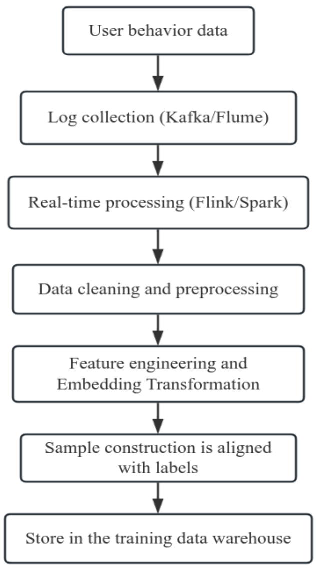

Figure 2. Data Processing Flowchart.

This process completes the full-chain processing from the collection of basic logs to the final production of high-quality samples from data, ensuring the validity, timeliness and accuracy of the data samples for training the model, and providing effective data for the decision-making of AI deployment.

3.3. Model Training and Optimization Mechanism

Model training is an important link that determines the intelligent effect of the advertising placement system. A hybrid modeling method is adopted and combined with deep learning to accomplish the prediction of user behavior and the dynamic adjustment of placement strategies. Among them, the DIN structure or the DeepFM structure will be taken as the basic model, and the user features, environmental features and advertising features after Embedding will be taken as the input. The model output is a click probability of $\hat{y}$, and the optimization objective is to minimize the binary cross-entropy loss function:

$$\theta_{CTR} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \, log(\hat{y}_i) + (1 - y_i) \, log(1 - \hat{y}_i)] \quad (3)$$

Among them, $y_i \in \{0,1\}$ indicates the actual clicked label, and $\hat{y}$ is the prediction result of the model. During the training process, the issue of extremely imbalanced samples was addressed through resampling techniques, and batch normalization and dropout operations were applied to avoid overfitting. For the adjustment of the advertising recommendation strategy, the policy gradient algorithm is used to explore long-term benefits. The long-term accumulated benefits are measured by using user feedback, and the strategy parameters are adjusted based on this information to achieve the optimal function $J(\pi) = E_{\pi}[R]$. The training framework supports a combination of online and offline methods. It can correct the model parameters in real time through incremental data, enabling the model to maintain adaptability and timely responsiveness to dynamic environments.

3.4. Automated Decision-Making and Placement Control Engine

The automated decision-making and placement control engine, as the core of the AI advertising system, is responsible for end-to-end processing from prediction to strategic decision-making. The placement control system will continuously receive the attribute vectors, candidate advertisement lists and surrounding context information initiated by the customers, and make decisions and provide feedback within milliseconds. Based on the prediction and reinforcement learning strategy scores of CTR/CVR, adjustments are made on the bidding price to rank the candidate advertisements, thereby generating the placement plan and distributing it to the advertising platform. The distribution control system achieves high efficiency and low latency by using the parameter server architecture and vectorized computation techniques [5].

In the execution stage of the strategy, selecting advertisements based on strategy distribution sampling helps to balance exploration and exploitation, maintaining a dynamic equilibrium in the decision-making process. Furthermore, the system is embedded with a real-time monitoring mechanism based on feedback loops, which feeds data such as exposure counts, click-through counts, and conversion counts as real-time rewards into the strategy model to enable automatic iterative online updates. In addition, various adjustment measures are also combined, such as budget control, frequency limitation, bidding ceiling and cold start protection, etc., to prevent the strategy from deviating from the optimal or partially optimal state and causing waste of resources.

For experiments and multi-strategy comparisons, this module provides original A/B testing capabilities. It supports precise segmentation of user traffic and implementation in multiple strategies, and can monitor the performance of key KPIs of each strategy, such as click-through rate (CTR), conversion rate (CVR), revenue per thousand impressions (eCPM), return on investment (ROI), etc. In addition, this module realizes the automatic release and cancellation functions of policies. Once the performance of a certain policy is better than that of the current baseline policy, the traffic allocation is immediately adjusted to accelerate the application of policy updates. In conclusion, this module has achieved the full-chain automated iterative optimization of "prediction: decision-making: operation: feedback", playing a crucial role in empowering the transformation of advertising placement towards intelligence.

4. System Implementation and Engineering Deployment

4.1. System Development Environment and Technology Selection

To ensure the extremely high performance, scalability and deployment flexibility of the advertising placement optimization system, a comprehensive investigation of the platform technology was conducted during the initial design of the system. The microservice architecture was used as the overall form of the background, and the core service modules were developed respectively using two languages, Python and Java. Among them, Python is mainly responsible for model learning and data processing. Java is mainly responsible for providing high-speed response and ultra-large-scale concurrent control for online services. Distributed computing and storage are achieved through the Hadoop ecosystem and container orchestration platform. Model learning is calculated through GPU clusters. Meanwhile, when the model is inferred online, it is deployed to the Kubernetes (K8S) environment to provide horizontal scaling capabilities. The following Table 1 lists the technical selections of the main components:

Table 1. Technical Selection of Main System Modules.

Module category	Technical selection	Explanation
Programming language	Python/Java	Python is used for AI training, and Java is used for service logic
Data collection	Kafka/Flume	Achieve high-throughput data stream transmission and log collection
Real-time computing	Flink/Spark Streaming	Support millisecond-level data preprocessing and feature update
Model training	TensorFlow/PyTorch	Support the training of deep models and reinforcement learning strategies
Model deployment	TensorFlow Serving/ONNX	Realize online reasoning of the model and A/B experiment management
Task scheduling	Airflow/Argo	Control the data pipeline, training tasks and online process
Containers and Scheduling	Docker/Kubernetes	Support automatic service deployment, elastic scaling and resource isolation
Data storage	HDFS/ClickHouse	They are respectively used for sample storage and online feature query

Through the above combination of technologies, the system not only meets the high-performance requirements for processing massive data, but also has good maintainability and scalability, providing a solid foundation for subsequent iterations and rapid experiments.

4.2. Model Training and Online Deployment Mechanism

The core step is to carry out training and deploy the model to achieve intelligent decision-making capabilities for scenario-based advertising. This platform adopts a scheme of separating model training and deployment to achieve the model effect and system stability. The system prepares the action and advertisement click data of new users every day, combines it with the configured training sample data stream, and uses the GPU cluster to train the CTR prediction model and reinforcement learning strategy model in parallel. This training is carried out using the TensorFlow framework, which supports distributed training, incremental training, and hyperparameter search, and can monitor evaluation metrics such as AUC and LogLoss in real time, serving as an important reference for model performance indicators. The trained model is automatically deployed by TensorFlow Serving or the self-developed inference engine. In the online calculation stage, the featured platform is mainly responsible for providing real-time features to the client and the environment/advertisements. The model service provides the pre-estimated data calculation results to the automated decision engine with a response time of seconds. This process includes version control, A/B testing, and progressive release functions, ensuring that the new model has a controllable impact on the business when it goes online. Through feedback loops, the utility of the model is continuously enhanced, ultimately achieving a closed-loop iteration.

4.3. Engineering Implementation of the Automated Decision-Making System

The automated decision-making system is a key application component of AI advertising platforms for implementing intelligent placement. The strategies in the system should be accurate and possess highly reliable and stable response capabilities under conditions of high parallelization, massive data flow, and extremely low latency. The system adopts the design and deployment mode based on the microservice structure, runs on the Kubernetes container scheduling system, and has a very high elasticity capability and disaster recovery capability. When AI is deployed, each user demand enters the system. First, the traffic acquisition layer processes and divides the data requests. Then, the requests are sent to the feature extraction module to obtain temporal user portraits, scenarios, historical behaviors, and creative features, and these features are passed into the already deployed AI model for reasoning. Key indicators such as CTR, CVR, and the potential value of advertisements are obtained. Based on the reinforcement learning strategy network, the advertisements are comprehensively scored using the prediction results, and the final decision results, namely the selection of advertisements, bids and rankings, are output.

After the strategy is generated, the system's management module will review the legality of the actions, considering how the budget is applied, frequency control, and constraints such as initialization protection and material exposure limits, ensuring each delivery meets the customer's goals without posing risks to the platform. Once the placement is confirmed to start, its effect will be directly pushed to the front end for presentation through Digital Performance Indicators (DPI) or the platform's internal channels, and this exposure behavior will be recorded immediately. After the release is completed, real-time collection of users' next reactions, such as clicks, conversions, stays, pop-ups, etc., is then fed back to the Kafka message stack for data backflow, model learning, and strategy iteration. During this process, the system contains a high-precision monitoring link, which can track the response delay, model score distribution, abnormal actions and other situations at each stage in real time to maintain the knowability and controllability of the system. Meanwhile, the decision throughput is improved through technical means such as batch predictive model services, asynchronous IO scheduling, and high-frequency buffer flushing, achieving a second-level deployment process in the overall deployment progress (see Figure 3).

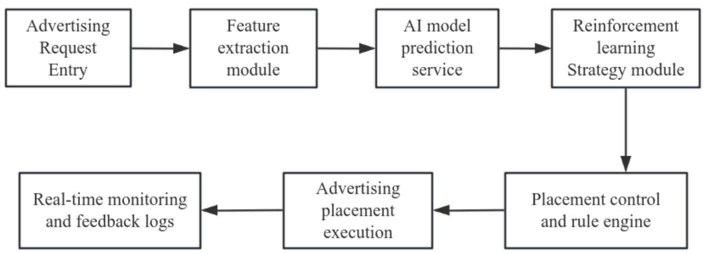

Figure 3. Component Diagram of the Automated Decision-Making System.

Through the above program structure and optimization strategies, the automated decision-making system realizes the intelligent processing of the entire process from "request input" to "result output" in the advertising placement system. It has strong load capacity and learning ability, and can support precise advertising placement and strategy adjustment under the business scale of hundreds of millions of requests.

5. Conclusion

This paper mainly focuses on advertising placement optimization and automated decision-making based on AI. With deep learning and reinforcement learning as the foundational theoretical system, and data management, model training, policy adjustment, and placement implementation as the main technical framework, this study systematically constructs and elaborates the approach. It demonstrates that AI can indeed improve the efficiency of advertising response, resource utilization, and intelligent decision-making. In the future, with the expansion of large-scale models and various information technology applications into multi-media placement, personalized customized creation and other fields, Advertising technology will continue to develop intelligently.

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