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Research on the Path and Efficiency of Empowering Accurate Advertising Delivery with Data Infrastructure

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Abstract: Now that the spread of advertisements is controlled by algorithms and changes happen in real-time, we no longer only need to store and report the data. It can help us understand the audience, create a model, update bidding plans, ensure compliance with regulations, etc. To solve the problem of how to use data infrastructure to improve the efficiency of targeted advertising, a closed-loop system has been built covering first-party data collection, unified identity resolution, timely provision of feature libraries, CTR/CVR prediction, budget bidding, attribution feedback, privacy management, etc. Offline Replay was carried out to compare the difference between the old batch processing and the new real-time feature service pipeline. Therefore, through the addition of identity graphs, feature libraries, streaming updates and feedback loops, the AUC has gradually increased from 0.763 to 0.821, the P95 response latency has dropped from 210ms to 98ms at 16kQPS, and ROAS has risen by 18.7%. Research shows that there are problems with the models of target advertising, and many people think these problems are due to low-quality data, outdated features, inconsistent engineering and privacy-constrained infrastructure.

1 Introduction

The development of the digital advertising market is now trending in the direction of measurability, automation and intelligence. According to the annual report released by IAB/PwC last year, by 2025, the amount of advertising revenue in the US Internet sector will reach approximately 300 billion US dollars, and the main reasons for this growth will be five factors: AI-driven development, retail media, search, video and first-party data strategies [1]. In other words, the competition of advertising has shifted from being centred on a single creative idea, a single channel or a single form, etc., to encompassing all types of capabilities such as data and algorithms, engineering, compliance, and so on. Now, the goal of precise location is no longer to identify people near the target; rather, it is to understand the conversion effects, marginal values, budget use, frequency control restrictions and privacy boundaries of users in a millisecond-level bidding window.

Data infrastructure can build various kinds of intelligent models according to different business

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demands. Only after the data of advertisers, such as membership, transactions, browsing, content interaction and customer service, are cleaned, labelled, associated, characterised and provided in real time can they serve as decision signals that models can understand, bidding systems can use to call, and operation staff can interpret. Recently, research on the value of single-party data has found that advertisers are paying more and more attention to data they can collect directly or obtain with user consent, such as purchase history, preference statements and in-site behaviour; it is better than general data in terms of personalisation effect and trust maintenance [2]. Therefore, precise targeting is not to add more external tags; rather, it should be about building a governable, traceable, updatable and measurable one-party data closed loop.

Recently, some research has been carried out in the field of CTR prediction, real-time bidding, privacy protection and federated learning. There is still a relatively large gap in engineering practice; the focus of model papers has been on algorithm accuracy, research on advertising management is about consumer response, and platform engineering literature is about system throughput. There are several problems with the actual operation of advertising companies, such as dispersed data in all sorts of systems, outdated functions, inconsistencies between offline and online data, slow attribution feedback, compliance risks, etc. Therefore, the advertising delivery chain will be used as the subject of this paper, and the data infrastructure is regarded as an "efficiency generation mechanism" in the four-aspect analysis of current status, problems, strategies and experiments. The three main contributions are: First, it has laid the foundation for the data infrastructure support of real-time bidding; Second, an efficient evaluation system that covers identification, feature construction, prediction, bidding, feedback and governance has been built; And Third, through offline replay experiments, it has been shown that improvements in infrastructure can increase AUC, LogLoss, response latency, CTR and ROAS.

2. Current Status Analysis of the Research Topic

2.1 Targeted advertising shifts from tag matching to real-time decision-making

The first type of targeted advertisement is based on the demographic information, location, interests, third-party audience profiles and so on; it is called a "match" of media resources and audience profiles, and this model can only be realized when there is a large amount of data and stable cross-site tagging. There are three defects in high-frequency real-time bidding: First, the granularity of the tags is too coarse and cannot reflect a user's immediate intention at different times, in various channels and contexts; Second, due to the slow update speed of the tags, users who have already purchased products are tracked and targeted multiple times, and their short-term interests cannot be captured; And third, due to the complexity of tag sources, there are problems with compliance, bias and a lack of interpretability.

The spread of the advertising system now has reached a high level and relies on how far it is disseminated. A single bidding request usually has signals from all these places: the user, the content, the ad, the context and the market. The system should be able to complete the functions of feature reading, model inference, bid calculation, frequency control judgment and log saving very quickly after receiving these signals. Research shows that in the construction of federated learning and edge data architecture for intelligent advertising, the efficiency of data flow, resource consumption, privacy protection and model accuracy should all be considered in the same architecture; otherwise, the advantages of model experimentation will not be realized in terms of online delivery revenue. Therefore, the reason for the effectiveness of precise targeting is that not only are the quality of the model parameters high, but also stable, fast and compliant delivery of signals can be achieved by the data infrastructure to the decision-making process.

Table 1. Core Levels of Data Infrastructure for Precise Advertising Targeting.

Layer	Core Module	Input Data	Primary Function	Effect Metric
Collection	Consent Event Pipeline	View, Click, Cart, Order	Capture first-party signals	Coverage Rate
Identity	ID Graph & Resolution	Login ID, Device ID, CRM ID	Unify audience entities	Match Rate
Feature	Offline/Online Feature Store	Profiles, Context, Ads	Serve consistent features	Freshness / Missing Rate
Model	CTR/CVR Prediction Service	Feature Vectors	Estimate response probability	AUC / LogLoss
Decision	Bidding & Budget Engine	pCTR, Bid, Constraint	Select and price impressions	ROAS / CPA
Feedback	Attribution & Experiment Loop	Conversion, Revenue, Exposure	Update learning signals	Incremental Lift
Governance	Privacy & Quality Control	Consent, Policy, Audit Logs	Reduce compliance risk	Risk Score

As shown in Table 1, the data infrastructure is not a database but a whole system covering all links of the advertising chain: before, during and after. The Collection Layer selects which signals to use and where they come from; the Identity Layer is to keep the same user information in all parts of the platform; the Feature Layer keeps offline training and online inference in sync; the Model and Decision Layer can directly reflect the efficiency of CTR, CVR and budget; the Feedback Layer knows how quickly the model learns from campaign results, etc.; the Governance Layer is responsible for determining the range of data usage. If a layer is missing, the target advertising will be either that the model is usable but the business is ineffective, or that it is effective in the short run but unsustainable from a compliance perspective.

2.2 Changes in the Data Supply Structure under Privacy Constraints

Privacy protection technology and the browser policy have changed the supply of advertising data. Based on the measurement of actual deployment for the Topics API, it can be seen that some advertising-related third parties have started to test the interest topic mechanism on real websites, but at this early stage, there are problems such as consent management, abnormal calls and integration errors [4]. At the same time, studies on the mechanism of interest disclosure have also found that there is a risk of re-identification after a long period of monitoring and cooperation by many parties, even without traditional third-party cookies [5]. It can be seen that privacy-friendly advertising is not just another name for the identifier in cookies; instead, the advertising system should control data minimisation, consent links, feature retention, model interpretability and audit trails in its architecture.

In light of this, the strategic value of one-sided data is high, but it cannot be assumed that it is high-quality data. The membership data contains high-value users and is relatively clean; the anonymous traffic has low value, the site browsing data is both timely and noisy, the transaction data is authentic and reliable but slow in time, and the customer service and content interaction data are rich in semantics but have high structuring costs. The data infrastructure needs to collect all kinds of signals in one system of entities, events, features and tags, record their time stamps, sources, permissions, quality indicators, etc., and also regulate the scope of their use. Therefore, in the future, in order to achieve precise targeting, one should cease using external tags and construct one's own governed data assets, continuously modify the attributes of data in the real-time chain for decision-making, etc.

2.3 The trend of combining CTR prediction research with engineering implementation

CTR prediction is still a basic problem of precise advertising. Recently, CTR models have been divided into shallow interaction models and deep learning models, and it is believed that high-dimensional sparse features, complex interaction relationships, long sequence behaviour and evaluation coordination have become the main problems [6]. In terms of the structure of the model, the expanded Transformer can expand the range of feature interaction for similar samples and is relatively good at predicting long-tail samples [7]; the Deep Context Interest Network can give more weight to the display context surrounding click behaviour and has shown the advantages of context-interest modelling in industrial systems [8]; the Deep Pattern Network extends user behaviour from a single event to the level of behavioural patterns to improve the expression of habitual interest [9], and the Deep Conversation Heterogeneity Perception Network focuses on how differences in interest within a conversation affect CTR prediction [10]. Taken together, these studies have shown that the exact advertising model has developed from the original single-sample feature splicing to the current multi-layer expression of context, sequence, retrieval, pattern, and so on.

To make good use of the new model, all-weather roads will be built. If the feature library does not have real-time behaviour data, the sequence model will be unable to recognise the present interest. If the features of the offline training are different from those used in the online service, the improvement in AUC will not be realised after deployment. If the attribution chain cannot quickly return the results of orders, lead generation and registration, the model will only be based on click signals and miss actual conversions. Therefore, in this study, we will not choose one specific CTR model; rather, we will construct a basic data acquisition and high-concurrency request management system that can constantly collect new data and handle a large number of high-concurrency requests reliably to support iterative learning based on the reasons mentioned above.

3. Raise questions

3.1 Data fragmentation leads to insufficient targeting identification and feature representation.

Data systems that advertisers commonly use include CRM, CDP, order systems, website tracking, app tracking, customer service systems, advertising platform reports, content management systems, etc. Because of the various business requirements of different systems, they have been built in different ways; therefore, there are differences in field standards, user IDs, time granularity and permission settings. As a result, there is no single view of the users in the advertising systems. The same user can be recognised by a phone number in the CRM, a device ID in the app, an anonymous exposure flag from the advertising platform and a membership number in the order system. Due to the lack of proper identity verification and event normalisation, the model can only obtain partial information, and thus the advertising decision often chooses a tag with high coverage but low precision.

The probability of a click per impression in ad response prediction can be written as:

$$pCTR_i = \sigma(z_i),\ z_i = \beta_0 + \beta^T x_i + g\theta(s_i, c_i, a_i) \quad (1)$$

As shown in formula (1), $pCTR_i$ represents the click-through rate for each exposure; it is modelled by the sigmoid function as , the dynamic feature term is represented as , the latest user behaviour sequence is shown by , the context scenario by , and the ad creative and product attributes are also included in this type of variable. The final result $g\theta(\cdot)$ is the parameter table for DAE. Based on the above formula, precise targeting does not use user information but rather considers all the data in the model to determine how broadly to expose.

3.2 Insufficient feature timeliness causes a discrepancy between model accuracy and deployment efficiency.

A good Signal in Ad Delivery is very short-lived. After a user has been viewing a product category for a long time, added an item to their shopping cart or read an article, there will be a relatively high probability that they will be shown related advertisements at this time; However, many hours or even a day later, it is no longer clear which users have a strong intention to purchase. The old batch processing method is T+1 for user profile generation; it can be used for report analysis but not for millisecond bidding. Real-time feature libraries are used to collect all kinds of attribute data about users in a stream and build a model that can accurately assess the current state of a user for inference, such as how many times they have clicked and viewed category information recently, how frequently they use the platform, how long it has been since the last purchase, etc.

In real-time bidding, the amount of money for an advertisement is determined by the probability of clicking, bids and quality coefficients; it can be considered a weighted function of these factors.

$$eCPM_i = 1000 \times bid_i \times pCTR_i \times q_i \quad (2)$$

As shown in equation (2), bid_i is the advertiser's base bid for exposure i, $pCTR_i$ is the predicted click probability of the model, and q_i is the quality coefficient or conversion quality correction term. If $pCTR_i$ is underestimated due to feature lag, then high-value exposures will be overlooked, and vice versa; that is to say, if it is overestimated, the budget will be wasted. It can be seen from the above data that timely changes in features are related to bidding rank and media cost.

3.3 There is an engineering consistency gap between offline optimization and online services.

One reason why many advertising systems work well in offline tests but are unstable after being put into operation is the lack of consistency in the data used for offline training, online feature services and online log feedback. For example, the offline training data is used to determine if an advertisement has been converted into a tag one day after exposure; only clicks are used for online budget control; and some fields are missing in the online inference stage. Therefore, the model's evaluation indicators will no longer be reflected in business indicators.

There will be a certain delay in real-time links. The whole service latency is divided into the following parts:

$$L = L_i + L_j + Lf + Lm + La + Ll \quad (3)$$

L is the end-to-end latency of a single request; L_i is the data access latency, L_j is the identity association latency, Lf is the feature reading latency, Lm is the model inference latency, L_a is the bidding ranking latency, and L □ is the lo
of time, it will be selected as the default bid or a coarse-grained audience strategy. Therefore, at the same time, we also need to reduce latency and improve model accuracy.

4. Problem Solving/Strategies

4.1 Constructing a one-way data closed loop and a unified identity graph

To address the problem of scattered data, the first step is to construct a closed-loop system that handles the collection of user consent, event information, identity resolution, feature creation, etc. Advertisers need to normalise the mapping of in-site browsing, search, add to cart, order, membership benefits, customer service inquiry, content interaction, etc., into a standard event model and record metadata such as event_time, user_key, device_key, campaign_key, source, consent_scope and quality_score for each event. Identity resolution should not only consider the maximum match rate; deterministic and probabilistic matching should be dealt with separately. That is to say, login ID, member ID and order ID should be used as high-confidence primary keys, and device ID, browser fingerprint and advertising platform identifier should be used as weak association signals in the authorised scope.

The goal of the unified identity graph is not to collect all the personal information of users indefinitely, but rather to convert the usable information from all aspects of interaction into auditable advertising decision assets. Set the length of the interest period, the life value of customers and repurchase cycles for logged-in users. Anonymity of a user can be deduced from the analysis of page context, current behaviour, path history and content semantics. If there is a restriction, then group statistics, aggregated interests, contextual targeting and federated learning can be employed for analysis. Thus, it is possible to increase the number of users and the quality of their attributes while meeting the requirements.

4.2 Ensuring consistency between offline training and online inference using a feature library

Feature libraries are the first part of data engineering for advertising algorithms. Offline feature libraries are employed to store historical samples, wide tables, labels, training snapshots and so on; online feature libraries provide the latest features in real time. Both need to have the same feature definitions, the same time windows and the same way to handle missing values so as not to be inconsistent with training and application. For advertising operation support, feature libraries should be able to handle numerical and categorical features, as well as sequence features, contextual features, creative features, advertiser budget features, etc. They should also have a section to record feature lineage for simple auditing and rollback.

Subject to the budget constraint, the aim of the target system can be expressed as an optimisation problem that considers the four aspects of the budget: income, expenditure, delay and privacy. In other words, it wants to know the target plan that can maximise the return on investment and meet all the relevant indicators.

$$\max U = \Sigma_i(v_i p_i - c_i),\ \text{st}\ L \le \tau,\ \varepsilon \le \varepsilon_{max},\ B \le B_t \tag{4}$$

As shown in equation (4), U is the net utility of the campaign; v_i is the conversion value, p_i is the conversion probability, c_i is the cost per impression or click, τ is the real-time service latency threshold, ε_{max} is the upper limit of the privacy budget, and B and B_t are the budget already used and the total budget, respectively. According to the above rules, the advertisement has been optimised according to the limitations of engineering and regulation; now it no longer aims only for a high click-through rate.

4.3 Streaming computing and real-time feedback improve the speed of deployment closed loop.

The second reason to strengthen the construction of a data platform is that we need to move away from the old T+1 batch processing mode and adopt a new "batch-stream integrated" feature update mode. Streaming can immediately record the information of an impression, click, add-to-cart and purchase in a message queue to update the new feature in near real time. The above are almost real-time and are then added to the online feature library. The three functions of the ad placement mechanism are: to seize the moment when people's buying intention shortens rapidly (e.g., after more than 10 minutes of continuous viewing of a product), to control the frequency and filter, which are stopped for those who have already purchased, and to quickly get experimental feedback or observe the differences in audience response of various creative groups during the promotion period can be all achieved every hour.

The closed-loop feedback system should be able to distinguish between clicks, shallow conversions and deep value. CTR is a single indicator, so there is a risk that people will be misled by sensational titles. All of the above should be taken into account to assess the actual impact of the advertising. Click Attribution, Pageview Attribution, Multi-touchpoint Attribution and Incremental Experiment can be used to find out the extra influence of ad reach. For industries that have a high value addition but a low frequency of transactions, both short-term agency indicators and long-term value labels can be used together in the model to reduce the learning difficulty caused by sparse feedback.

Table 2 Experiment Setup for Offline Playback.

Item	Configuration
Sample Window	30 days of anonymized ad logs
Impressions	4,000,000
Positive Rate	1.86% clicks, 0.21% conversions
Split Strategy	Time-based 70% train / 15% validation / 15% test
Feature Groups	User, Context, Ad, Creative, Session, Budget
Baseline Model	GBDT + Logistic Regression
Deep Model	DeepFM with sequence and context features
Serving Baseline	Batch profile table
Serving Upgrade	Online feature store with streaming updates
Metrics	AUC, LogLoss, P95 latency, CTR lift, ROAS lift

Table 2 is the basic experimental setup. Not to divide randomly, a division based on time was used in the experiment to simulate the actual situation of applying historical data for prediction after the beginning of the advertising system. Batches of the control group were used for profiling and the old GBDT+LR model was used; the experimental group started at the beginning with identity graphs, online feature libraries, streaming updates and feedback loops. In addition to model accuracy, the speed of service and the level of business operation were also considered when assessing the advertising system. As there were no logs from the private company, experimental data were anonymised and replayed offline according to the structure of the public CTR task field. The results will only be used for the purpose of method evaluation and will not be applied to any specific company.

Figure 1 is the change in AUC for the five link schemes. The baseline AUC of only the batch-processed profiles is 0.763. With the addition of identity graphs, cross-touchpoint user recognition capability has increased and the AUC is now 0.781. Add a feature library to make the offline training and online inference more consistent and thus improve the AUC. According to the recent popularity of the model, it will be released in a closed loop and constantly optimising to enhance the quality of conversion tags. Based on the above results, it can be concluded that the advantages of precise targeting stem from many factors, and their realisation is the result of the continuous improvement in data coverage, timeliness of features, etc.

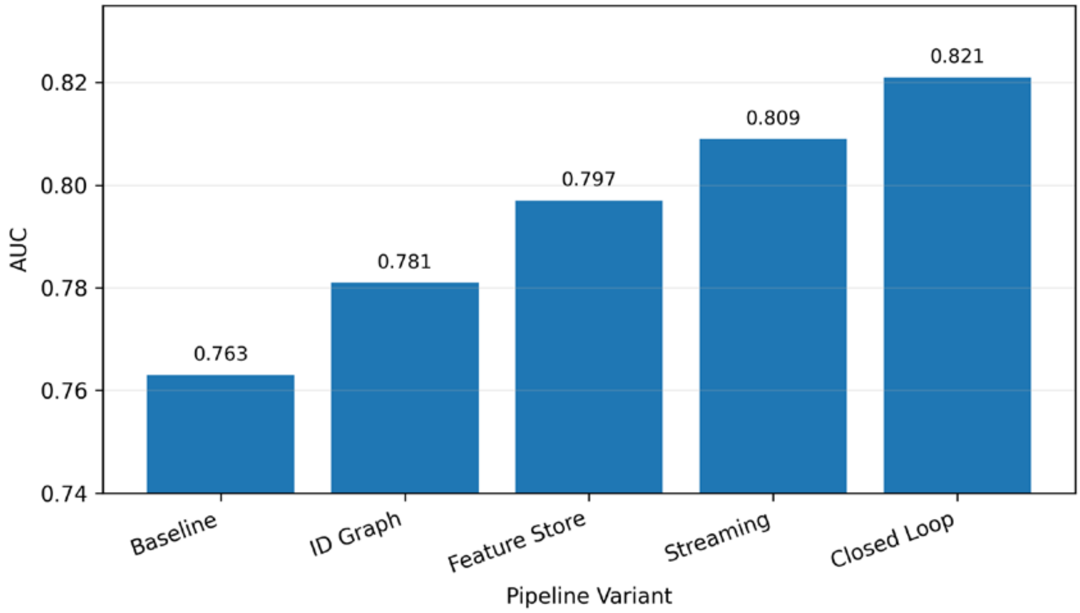

Figure 1. Changes in AUC After the Gradual Improvement of Data Infrastructure.

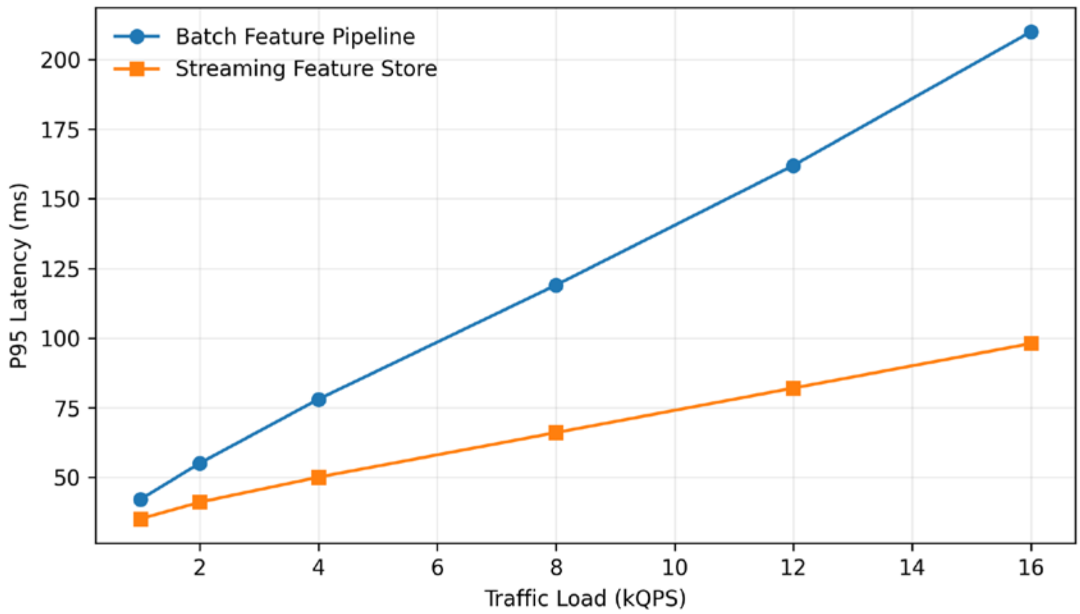

Figure 2. Comparison of P95 Response Delay at Different Flow Rates and Pressures.

Figure 2 compares the P95 latencies of the two feature processing links at different kQPS loads; they are the batch processing feature link and the real-time feature library link. As the number of queries per second (QPS) increases from 1kQPS to 16kQPS, the delay of the batch processing link will be approximately 42ms and 210ms, respectively, because of the added logic for feature query, completion and degradation. The pre-compiled, cached and incrementally downloaded library for the real-time function has been kept up to date to ensure that the P95 latency is 16kQPS or less than 98ms. Therefore, it is necessary to improve the quality of data infrastructure and ensure the stability of business service under high concurrency.

Table 3. Summary of the Test Results for Different Links.

Variant	AUC	LogLoss	P95 Latency (ms)	CTR Lift	ROAS Lift	CPA Change
Baseline	0.763	0.438	210	0.0%	0.0%	0.0%
ID Graph	0.781	0.421	186	+4.1%	+5.8%	-3.2%
Feature Store	0.797	0.409	142	+7.6%	+9.4%	-6.1%
Streaming	0.809	0.397	118	+10.9%	+13.6%	-8.4%
Closed Loop	0.821	0.382	98	+14.8%	+18.7%	-11.3%

Table 3 shows that the closed-loop model improved the engineering and business indicators compared with the baseline model. The increase in AUC is 0.058 and the decrease in LogLoss is 0.056, so the predicted distribution is relatively close to the actual click results. P95 latency decreased by 112 ms, and from this, it can be seen that adding more functions to the real-time model did not improve the service performance. CTR Lift and ROAS Lift were 14.8% and 18.7%, and CPA fell by 11.3%. At the same time, in order to improve the accuracy of recognition and provide more indicators for the analysis of budget utilisation efficiency, the data infrastructure will be strengthened and a complex model will not be required.

4.4 Ensuring long-term effectiveness through privacy governance and quality control

Precise Targeting is to be in line with privacy regulation. At the source of data collection, the advertising system should have a consent manager and specify the purpose, storage period and sharing conditions for each piece of data. At the level of features, sensitive attributes should be anonymised, grouped and aggregated, differentially private, etc. At the level of the model, feature importance, group fairness and anomaly detection can be used to find any discrimination or over-targeting. At a very sensitive time for the target group, individual tracking should be reduced and instead contextual targeting and aggregated audiences used.

In order to assess whether the investment in infrastructure has increased efficiency, both gains in business and costs of infrastructure should be included in the index.

$$\eta = \Delta ROAS \ / \ ROAS_0 - \lambda C_i / C_m \tag{5}$$

As shown in Equation (5), η is the net efficiency of the infrastructure, ΔROAS is the increase in ROAS after the upgrade, ROAS0 is the advertising return on the baseline link, Ci is the data infrastructure construction and operation cost, Cm is the media placement cost, and λ is the cost penalty coefficient. When $\eta > 0$, it means that the placement revenue generated by the infrastructure can cover its resource investment; if η is close to 0 or negative, then we need to reconsider the complexity of the feature, the real-time calculation frequency and the model service cost.

Quality control will damage the company. Traffic in ad logs is bot traffic, accidental clicks, duplicate impressions, abnormal conversions and attribution pollution. If there is noise in the training set, the model will learn to recognize incorrect click patterns and thus have good short-term metrics but poor actual conversion rates. Data infrastructure should have traffic cleaning, anomaly detection, sample deduplication, delayed conversion rewriting, anti-fraud rules, etc., and the quality score can be used as a model feature or training weight. Turn the data into more reliable information and the targeted advertisements will no longer be useless follow-up campaigns.

5. Conclusion

Based on the research results of the path and effect of data infrastructure-driven precise advertising targeting, first of all, the ability of precise advertising targeting has moved from using external tags to building a closed-loop data system. The seven are: data collection, identity resolution, feature library, model service, bidding decision, attribution feedback and privacy management, etc. Secondly, the new facilities will be more convenient to operate and improve the model. According to the results of the offline replay experiment, the closed-loop system performed better than the old batch-processing method; that is to say, at a query rate of 16kQPS, the AUC increased from 0.763 to 0.821, LogLoss dropped from 0.438 to 0.382, P95 latency fell from 210ms to 98ms, and as a result, ROAS rose by 18.7%. Thirdly, the Data Infrastructure will also be changed in the new model. Although the CTR model performs well, it does not have new additions, its indicators have remained unchanged, and it has not implemented a loop feedback mechanism; thus, business development will be restrained.

The data above show that the effect of targeted advertising should not only be evaluated by CTR and AUC, but also by other factors such as ROAS, CPA, latency, coverage, feature missing rate, compliance risk and infrastructure cost. Advertisers should not be tempted to increase the range of data collection indefinitely; instead, they should use the principle of necessity to collect only the minimum amount of necessary data, which is reasonably controlled and auditable. The first reason to use this platform is to reduce the deployment uncertainty of the model by means of batch and stream integration, feature reuse, online experimentation, privacy protection, etc.

Given that the data is open to the public and people are concerned about their own information privacy, this experiment was conducted offline by means of replay verification of the infrastructure path; therefore, it was not a multi-industry or multi-media platform long-term incremental experiment. In the future, true A/B tests and causal inference, federated learning and privacy-preserving computation will be used to study the effect of various data governance plans on all kinds of user groups and conversion rates, etc. With the emergence of generative AI creatives, retail media networks, cross-channel attribution, etc., the structure of advertising distribution has been changing, and we now need an intelligent operating system for all-weather marketing decision-making that can support various reasons.

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