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Research on Intelligent Prediction in Private Domains Based on Online Linear Models

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ABSTRACT
In recent years, China's internet ecosystem has continuously improved, with steady growth in user scale. As "public domain traffic" faces saturation, major retail banks and retail brands have turned to the "private domain traffic" user operation model to promote industrial growth and prevent customer churn. Online linear models can accurately predict user needs in private domains, thereby enabling more effective allocation of data elements, empowering intelligent governance of private domains, and facilitating the intelligent development of private spaces.

KEYWORDS
Big data; Private domain space; Online linear model; FTRL model

1 Introduction

1.1 Research Background

In recent years, China's internet ecosystem has continued to optimize, with user scale steadily expanding and the proportion of the private domain market gradually increasing. As an important component of China's socialist market economy, private domain space complements public domain space and represents a key area for future enterprise development. It not only helps traditional retail industries break through the limitations of public domain traffic but also optimizes resource allocation, enhances the efficiency of market-based resource distribution, and promotes the high-quality development of the digital economy. Given this, the importance of research on intelligent private domains has become increasingly prominent.

1.2 Literature Review

1.2.1 Exploring New Spaces for Intelligent Private Domain Development with Online Linear Models

Research on using financial data models and big data analytics to predict customer needs and improve resource allocation has received widespread attention in academia. Traditional private domain management often relies on time-series models (Challa et al., 2020) to predict product demand, with operational models primarily driven by experience. In recent years, as the digital economy has gradually become a core driver of national economic growth, research on intelligent private domains has shifted toward data-driven approaches. In the field of private domain management, machine learning models such as Random Forests and LSTMs, as well as online linear models represented by FTRL (Yang Zhengsen, 2019), have been introduced into demand forecasting models. These models have significantly improved prediction accuracy and laid a theoretical foundation for the development of intelligent private domains. However, early research had inherent limitations in algorithmic models. For example, the ARIMA model can only handle linear relationships and struggles to integrate heterogeneous features such as user profiles and social interactions (Wang et al., 2021). Furthermore, with the advent of the big data era, networked information data has exploded, intensifying competition in the retail and financial sectors. Online linear prediction models help drive efficient and precise business decisions by capturing key driving factors, enabling intelligent demand response, rational resource allocation, and automated precision marketing. The essence of private domain traffic is social customer relationship management (Social CRM), aiming to enhance repurchase rates, conversion rates, and maximize customer lifetime value through relationship management, thereby reducing enterprise operational costs and improving efficiency and profitability.

1.2.2 Online Linear Models Breaking the Data Governance Dilemma in Demand Forecasting

Utilizing demand forecasting models to explore the in-depth development direction of intelligent private domains has become a significant hotspot in contemporary private domain traffic research. Compared to public domain traffic, private domain space possesses more direct, repeatable, and low-cost user connectivity. Based on this, demand forecasting models, by constructing a "prediction-decision-feedback" closed loop, mine temporal patterns in user behavior and correlations among multi-source features, providing forward-looking decision support for intelligent private domain

research. Domestic studies discuss brand target consumer operations based on private domain traffic, suggesting that guiding and leveraging public domain traffic through private domain traffic is a key focus for future enterprise development. Additionally, research on private domain traffic in WeChat platform publishing based on the AARRR model indicates that in the next 5–10 years, private domain traffic will not only significantly promote the publishing industry but also gradually increase its penetration in highly digitized and competitive industries. Multi-modal fusion models are one of the key technologies in demand forecasting. Graph Neural Network models (Alibaba, 2023) incorporate community propagation paths into predictions, substantially reducing prediction errors for fission conversion rates; Transformer + spatiotemporal encoding (Yu Xinzhou et al., 2024) effectively controls the error range in demand forecasting. Ensemble models perform excellently in CLV prediction. Meanwhile, big data governance faces numerous challenges. To promote the application of demand forecasting models in intelligent private domain research, Ma M et al. employed sparse learning models like Lasso with minimum absolute shrinkage, aggregating data to capture heterogeneous market factors in panels, thereby reducing instability in Lasso's feature selection and partially meeting the real-time requirements of private domain traffic. In recent years, research on intelligent private domains has attracted considerable attention due to its important role in the transformational development of retail brands and retail banks. Wang Lei et al. (2022) pointed out that in the context of strengthening ESG development, data silos have become a major obstacle to corporate digital transformation and information integration. This poses a significant challenge to traditional ARIMA models, which can only handle linear relationships and rely on historical sales data while ignoring user profiles and real-time behavior. Classic machine learning requires integration of multi-source heterogeneous private domain data records. Wu Taixuan et al. (2024), based on an empirical analysis of 95 judicial cases, emphasized the potential threats of this practice to the control of commercial data elements and personal privacy protection.

1.3 Research Methodology

1.3.1 Literature Research Method

Fully utilize internet searches to collect academic works, electronic literature, and related resources, and conduct reading. First, read the abstracts of relevant literature to assess their relevance to the research topic. Then, classify the literature based on keywords, primarily "online linear model," "private domain space," "demand forecasting model," etc. Next, sort the literature according to its degree of relevance to the research topic. Finally, integrate the papers with the research questions to serve the study.

1.3.2 Logical Analysis Method

The main dilemma in private domain space governance lies in the limitations of traditional linear models, leading to lagging resource allocation by enterprises. Additionally, "data silos" hinder feature integration, resulting in high prediction errors. Based on this, to achieve precise demand response, it is necessary to break through the limitations of ARIMA models. By introducing multi-modal fusion architectures, such as combining the FTRL model with Transformer encoding, prediction errors for fission conversion rates can be significantly reduced.

Therefore, we choose to introduce online linear models like FTRL into intelligent private domain governance, which can effectively filter outliers in user data and achieve a balance within the ESG governance framework.

1.3.3 Case Study Method

Using Taobao's "You Gou" as the primary case, it demonstrates that online linear models, particularly the FTRL algorithm, can effectively handle private domain traffic data in e-commerce, providing strong support for precision marketing, inventory management, and customer relationship management, ultimately enhancing the operational efficiency and profitability of e-commerce platforms.

2 Research Content

2.1 Theoretical Foundation

First, intelligent prediction in private domains is based on multi-dimensional behavioral economics theories. According to loss aversion and framing effect theories, people exhibit asymmetry in psychological responses to gains and losses—the pain of a loss is far stronger than the pleasure from an equivalent gain (Ying Feihu, 2025). Research shows that the intensity of negative emotions from a loss is approximately 2–2.5 times that of positive emotions from an equivalent gain. This implies that compared to "discount promotions" in public domains, users are more inclined to pay for "expiring offer reminders" customized by brands in their private domains. Simultaneously, based on social identity and conformity

effects, people tend to do what others are doing, which can be understood as a higher acceptance of actions perceived as risk-free. In private domains, brands incorporate social influence into prediction features, greatly enhancing the accuracy of intelligent predictions. Furthermore, multi-objective optimization theory (Xiao Xiaowei, Xiao Di, et al., 2009) points out that to solve optimization problems with multiple conflicting objective functions, it is necessary to find a set of "Pareto optimal solutions," where no solution is superior to others in all objectives. Private domain issues involve multiple objectives, such as Gross Merchandise Volume (GMV), user experience, Customer Lifetime Value (CLV), and brand health. Therefore, to optimize private domain management, it is essential to combine the FTRL online linear model, leveraging its advantages in handling high-dimensional sparse features to maximize the sustainable development of private domain spaces.

2.2 Case Analysis

2.2.1 Case Background

Taobao You Gou, as an important private domain stronghold within the Taobao platform, faces challenges such as slowing growth in private domain traffic, weak user interaction, and low conversion efficiency. Against the backdrop of continuously rising public domain traffic costs, how to accurately identify high-value users and achieve personalized reach through intelligent means has become a core issue for improving private domain ROI.

2.2.2 Taobao You Gou Private Domain Ecosystem

Taobao You Gou initiated the construction of a private domain operation system, accumulating over 5 million private domain users through three core channels: store membership systems, corporate WeChat communities, and Taobao group chats.

The core objectives of its private domain operations are to increase user repurchase rates, reduce customer acquisition costs, and optimize marketing conversion efficiency. However, traditional operation models have obvious shortcomings: reliance on operator experience for strategy formulation, lacking data-driven precise predictions; crude segmentation of private domain users, leading to user aversion due to "one-size-fits-all" marketing outreach; uncontrollable promotional campaign effects, resulting in significant resource waste. Based on business pain points, Taobao You Gou identified three key prediction needs: first, predicting user repurchase cycles to clarify repurchase windows for precise outreach; second, predicting community activity levels to identify high-churn-risk communities in advance for intervention; third, predicting marketing campaign conversion rates to anticipate the effects of different campaign plans for optimized resource allocation. Online linear models, due to their strong real-time capabilities, high interpretability, and low deployment costs, became the preferred technical solution for its intelligent private domain predictions.

2.2.3 Implementation of Online Linear Models in Private Domain Scenarios

Taobao "You Gou" established an FTRL model with "the time interval until the user's next repurchase" as the prediction target. By inputting user value features and consumption behavior features into the online linear model, a corresponding repurchase window period can be output for each user. Users are classified by probability: for high-potential repurchase users, Taobao "You Gou" pushes exclusive discount coupons within the window period, avoiding frequent outreach; for medium-potential users, it sends "exclusive benefits for old friends" via community channels, combined with 1v1 customer service recommendations for suitable products; for low-potential users, it pushes membership point redemption activities to stimulate demand. Through precise classification and effective intervention, user repurchase conversion rates can be significantly improved. In community activity prediction and churn intervention, online linear models are typically used for emergency intervention in high-churn-risk communities: by analyzing user data using an online logistic regression model, with features such as current community daily message count, administrator interaction frequency, and benefit distribution frequency, communities are categorized into "highly active," "stable," and "high churn risk" tiers. For high churn risk communities, exclusive large discount coupons are pushed, and content 推送 frequency is adjusted simultaneously. Data shows that the 7-day retention rate of high-churn-risk communities predicted and intervened by the model can be effectively improved.

3 Conclusion

3.1 Case Results and Value

At the technical level, the interpretability of online linear models allows Taobao operations personnel to more clearly and intuitively understand factors influencing user behavior and make timely and effective judgments and measures. In

terms of core technical capabilities, based on Alibaba's "OneID" technology, cross-channel user identities are automatically linked to construct a global user ID graph. Leveraging the three major advantages of online linear model prediction algorithms—multi-objective prediction, sparse feature processing, and real-time updating mechanisms—helps break through user "data silo" problems, promotes private-public domain linkage effects, and further enhances the accuracy of intelligent private domain predictions.

3.2 Current Limitations and Optimization Directions

The current limitations in applying online linear models to intelligent private domain prediction mainly lie in weak adaptability to extreme scenarios and insufficient accuracy due to linear relationship assumptions. During special events like "Double 11" promotions, where user behavior fluctuates significantly, short-term prediction errors of the model increase. Subsequently, specialized model threshold systems can be established for such scenarios to calibrate prediction coefficients. For the numerous nonlinear correlations in user behavior, pure linear models cannot capture them, leading to insufficient prediction accuracy in some scenarios. Future work could combine online linear models with decision tree models to ensure both interpretability and accuracy in capturing nonlinear features.

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