Precision Advertising in WeChat Official Accounts Based on Click-Through Rate Prediction: A Postprint

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Abstract

[Purpose/Significance] This study aims to quantify the position of WeChat Official Accounts within social networks, predict the click-through rates of advertisements on these accounts, provide novel insights for the precise placement of WeChat Official Account advertisements, and improve advertising effectiveness.

[Method/Process] Based on an advertising click-through rate prediction model, this research utilizes the Analytic Hierarchy Process (AHP) to construct a comprehensive evaluation system for WeChat Official Account positions and determine indicator weights. Subsequently, it combines social network analysis methods to calculate specific values of evaluation metrics, thereby predicting the advertising click-through rates of WeChat Official Accounts to guide advertising placement.

[Results/Conclusion] The position of Official Accounts in social networks influences their advertising click-through rates, consequently affecting advertising effectiveness. Advertising placement should incorporate the position of Official Accounts within social networks as a consideration, guided by predicted click-through rates, avoid low-performance scenarios, and adopt differentiated placement strategies for Official Accounts occupying different positions.

Full Text

Abstract

[**Purpose/Significance**] This study aims to quantify the position of WeChat Official Accounts within social networks, predict the click-through rates (CTR) of advertisements on these accounts, and provide new insights for the precise delivery of WeChat Official Account advertisements to improve advertising effectiveness. [**Method/Process**] Based on an advertising CTR prediction model,

we constructed a comprehensive evaluation system for WeChat Official Account positioning using the Analytic Hierarchy Process (AHP) to determine indicator weights. We then combined this with social network analysis methods to calculate specific values for each evaluation metric, enabling CTR prediction to guide advertising placement decisions. [**Result/Conclusion**] The position of an Official Account in a social network influences its advertising CTR, which in turn affects advertising effectiveness. Advertising delivery should incorporate the social network position of Official Accounts, using predicted CTR as a guide to avoid low-performing placements and adopt differentiated strategies for accounts in different network positions.

Keywords: advertising CTR prediction model; analytic hierarchy process; social network analysis; location core degree; accurate ad delivery

Introduction

With the proliferation of mobile devices, mobile media and self-media platforms have attracted increasingly large fan bases, creating powerful fan effects. Advertising media have shifted from traditional channels to internet platforms, with traditional media outlets opening WeChat Official Accounts during their digital transformation, though with varying marketing effectiveness. Currently, this unique WeChat medium has not yet achieved precise ad delivery, resulting in mismatches between advertisements and Official Accounts and unsatisfactory advertising outcomes. How to achieve targeted and effective ad delivery on the WeChat Official Account platform has become an urgent problem to solve. This paper considers the position of WeChat Official Accounts within social networks as a key factor, using an advertising CTR prediction model to propose a precise delivery strategy for WeChat Official Account advertisements, aiming to improve delivery effectiveness and provide new approaches for targeted advertising.

WeChat Official Account advertising has transformed traditional advertising models, with interpersonal communication becoming central to this dissemination technology. The relationship between users and advertising media, as well as among different advertising media themselves, has fundamentally changed. Facing the impact of emerging micro-media platforms, traditional advertising's focus on attracting user attention suffers from uncertainty and ambiguity in target audiences. This paper addresses the challenge of precise ad delivery on WeChat Official Accounts by quantifying their position in social networks and predicting advertising CTR to guide placement decisions.

1 Research Status

Existing research on WeChat Official Platforms primarily focuses on factors influencing communication effectiveness. Ji Fang et al. used AHP to identify key factors affecting WeChat platform communication effectiveness, including fans, dissemination methods, and content, offering recommendations for improve-

ment. Fang Jing et al. studied information dissemination characteristics in user online community networks, finding that WeChat Official Account information dissemination networks are centralized community networks, and investigated how push frequency, timing, title length, and account theme affect information dissemination heat. Wu Zhongtang et al. used correlation and regression analysis to explore relationships between keyword popularity, semantic variables, and reading rates, as well as between reading rates and forwarding/collection rates. S. Shan et al. applied information dissemination theory and motivation theory to examine factors influencing haze information dissemination on WeChat. Xu Baoda et al. identified WeChat Official Account information dissemination networks as scale-free networks and proposed communication models.

In advertising delivery research, studies have concentrated on targeted placement strategies. B. Amit et al. incorporated user search behavior into models for behavior-based targeted advertising. E. Agichtein et al. achieved user-ad matching based on behavioral data for targeted delivery. Zhang Di implemented separate delivery strategies for long-term and short-term user behaviors. Cheng Longlong combined time-varying user behavior models with LDA topic models using user behavior time-series data to optimize behavior-based targeted delivery. For content-based targeting, M. Vanessa et al. improved content-keyword matching through machine learning. M. Ciaramita et al. achieved semantic associations between ad topics and webpages to enhance targeting accuracy. A. Broder et al. used semantic classification for both ads and webpages to calculate proximity and rank ads, overcoming pure syntactic analysis limitations.

While these studies identify specific influencing factors and marketing strategies for WeChat Official Platforms, they do not elaborate on how to achieve precise ad delivery for these platforms. Moreover, current advertising placement only considers ad position within content context, neglecting the advertising medium's position within social networks. How to utilize social networks for targeted ad delivery remains unclear. This paper addresses this gap by focusing on precise ad delivery based on Official Account positions within social networks, aiming to quantify node positions to improve predicted CTR and enhance advertising effectiveness.

2 Research Approach

Previous research on WeChat Official Account advertising has primarily explored marketing strategies. Huang Huan identified interactive marketing, event-topic marketing, and precision marketing as key strategies in micro-communication contexts. Zhang Rongrong noted that advertising delivery should divert traffic based on user needs to achieve precise targeting according to user characteristics, though without detailing implementation methods. Qin Zeyu et al. provided specific strategies including target group 锁定 and innovative ad planning.

Advertising delivery research has mainly focused on targeted placement. B.

Amit et al. proposed a user behavior-based targeting model incorporating search behavior metrics. E. Agichtein et al. achieved user-ad matching through behavioral data. Zhang Di implemented separate strategies for long-term and short-term behaviors. Cheng Longlong combined time-varying user behavior models with LDA topic models using temporal data.

Advertising CTR prediction estimates the ratio of ad clicks to total impressions given a user and advertisement, directly affecting ad ranking and influencing utility for users, media platforms, and advertisers. Current CTR prediction models fall into two categories: hypothesis testing-based and position-based. Bayesian network models are widely used hypothesis testing approaches, positing that ads are clicked only when seen and relevant to user needs. The click chain model is another hypothesis testing approach that models user click processes using ad-query relevance and probability of viewing subsequent ads as posterior parameters.

Ads in different positions exhibit significantly different CTRs. Users notice prominently positioned ads first, so high CTR doesn't necessarily indicate high relevance. Thus, position-based CTR prediction models emerged. Logistic regression is a typical position-based model that incorporates position factors as parameters, assuming each ad click is an independent event. Different positions yield different CTRs. Given this paper's focus on how node positions in citation networks affect advertising CTR, we adopt a position-based CTR prediction model for network-level analysis.

We analyze effective WeChat Official Account ad delivery using CTR prediction models. Traditional models only consider ad position within content context, whereas this paper introduces node position within citation networks. Using AHP to construct a location core degree evaluation system and calculate weights, combined with social network analysis to determine indicator values, we use Matlab for CTR prediction and trend analysis.

Specifically, as shown in Figure 1 [Figure 1: see original paper], our research approach combines node positions in citation networks with CTR prediction models to quantify node positions, enabling effective ad delivery from both local subnet and whole-network perspectives.

3 Establishment of Analytic Hierarchy Process

Social network analysis measures overall network structure and node positions through various metrics. This study selects node position metrics (including centrality analysis, core-periphery analysis, and K-core analysis) to quantitatively evaluate node positions in social networks.

Social network analysis examines social structures and relationships by analyzing network connections to understand node attributes and network structures. Node positions can be measured by centrality, K-core values, and core-periphery values. Centrality analysis includes degree centrality, betweenness centrality,

and closeness centrality. In organizational informal networks, members with higher degree centrality have more connections, greater information exchange opportunities, and may become network centers. High betweenness centrality indicates actors occupy structural holes controlling information transmission. Higher closeness centrality means longer paths to access other members, making knowledge acquisition more difficult. High closeness actors occupy peripheral positions. K-core analysis stratifies nodes from core to periphery. Core-periphery structure describes networks with tightly connected centers and sparsely connected peripheries, where core degree directly represents an account's centrality.

Based on calculation methods, indicators are categorized into micro-position and macro-position metrics. Degree and betweenness centrality measure node connections with surrounding nodes, reflecting importance in local networks, thus classified as micro-position. Closeness centrality measures path lengths to other nodes across the entire network. K-core analysis emphasizes node connections throughout the whole network. Core-periphery analysis identifies core and peripheral regions. These three indicators address the whole network, thus classified as macro-position.

The node position evaluation system provides standards for quantitatively describing positions using analytical data, enabling position quantification for subsequent CTR prediction. The system has three layers: the goal layer (position) to describe each node's position numerically; the middle layer (micro-position and macro-position) that jointly determines final position; and the bottom layer comprising specific indicators: degree centrality, betweenness centrality, closeness centrality, K-core value, and core-periphery value. The final hierarchical evaluation system is shown in Figure 2 [Figure 2: see original paper].

4 Research Implementation

4.1 Research Object Selection

This study selects hot WeChat Official Accounts as research objects, building a social network based on article reposting relationships among accounts. Using social network analysis, we calculate specific position evaluation indicator values to quantify account positions and analyze how to achieve precise ad delivery based on predicted CTR.

Data sources should have two characteristics: large fan bases (making position factors more significant) and substantial article accumulation (forming the basis for citation network analysis). We selected the WeChat Official Account Monthly Ranking from Qingbo Index, recognized as a top big data think tank by the National Information Center in 2017. The ranking list is authoritative and credible. We obtained hot WeChat Official Account data from Qingbo Index's October 2017 ranking.

The Top 50 accounts first satisfy the large fan base requirement. After verifying article accumulation, we examined each Top 50 account's historical posts. All

met the requirements, so we selected the Top 50 ranked accounts as research objects. Table 1 shows the research objects and their rankings.

Using the historical message search function, we retrieved each account's posts by searching account names. We collected statistics on reposting situations, using repost counts as connection weights to establish edge relationships between accounts. After normalization using Matlab, we obtained the weighted adjacency matrix for the directed article reposting network, shown in Table 2 .

4.2 Social Network Mapping Construction

Using social network analysis tool Ucinet 6.0 and the normalized weighted adjacency matrix, we conducted visual analysis to construct the Official Account article reposting network graph, shown in Figure 3 [Figure 3: see original paper].

4.3 Micro-Position Indicator Calculation

Micro-position indicators include degree centrality and betweenness centrality. Using Ucinet for analysis, we obtained results shown in Table 3 .

(1) Degree Centrality. Overall, degree centrality varies significantly among accounts, with bottom-ranked accounts having values of 0. The top 10 accounts by degree centrality are shown in Table 3. People's Daily, Xinhua News Agency, and Outlook Think Tank have high degree centrality exceeding 50, indicating they are core accounts in the network—sources of citations for other accounts and occupying central positions. People's Daily has the highest degree centrality at 67.347, demonstrating absolute advantage in the citation network with high reposting volume and core network status.

(2) Betweenness Centrality. In the article reposting network, betweenness centrality represents an account's control over content dissemination. Overall, except for People's Daily's absolute advantage, other accounts show small differences. The top 10 accounts by betweenness centrality are shown in Table 3. People's Daily, Xinhua News Agency, and China Search have high betweenness centrality above 8.8, controlling network content flow. Betweenness centralization measures the gap between the highest and other nodes; a higher value indicates information dissemination may overly depend on certain nodes. Network analysis shows a betweenness centralization of 23.74%, indicating multiple information sources exist.

4.4 Macro-Position Indicator Calculation

Macro-position indicators include closeness centrality, K-core values, and core-periphery values. Based on the reposting network graph, we calculated these using social network analysis methods, with results shown in Table 4 .

4.4.1 K-Core Analysis Figure 4 [Figure 4: see original paper] shows K-core analysis visualization, where red represents core nodes and green represents pe-

ripheral nodes. Colors transition from red, gray, rose-red to dark blue, indicating decreasing coreness. Peripheral nodes are mostly isolated and not discussed further.

Table 4 shows K-core analysis results. People's Daily, CCTV News, Xinhua News Agency, CCTV Finance, People's Daily Online, Zhanhao, China Government Network, China Search, Reference News, and Global Times occupy absolute core positions in the citation network.

4.4.2 Core-Periphery Analysis Core-periphery analysis identifies core and peripheral Official Accounts, with core degree directly representing account centrality. Analyzing Table 4 results shows core accounts identified by core-periphery analysis basically match those from degree centrality and K-core analysis. Core network positions are consistently held by CCTV Finance, People's Daily, CCTV News, Xinhua News Agency, Hangzhou Traffic 918, China Search, People's Daily Online, Communist Party Member, Zhanhao, and China Government Network, with only ranking variations.

5 Weight Determination and CTR Prediction

5.1 Evaluation System Weight Determination

Let $X_1, X_2, \ldots, X_p$ represent random variables with sample observations $x_1, x_2, \ldots, x_p$. If we can find coefficients $c_1, c_2, \ldots, c_p$ satisfying:

$$\text{MaxVar}(c_{1X}1 + c_{2X}2 + \cdots + c_{pX}p) \quad (2)$$

subject to:

$$c_1^2 + c_2^2 + \cdots + c_p^2 = 1 \quad (3)$$

This maximizes variance, and since variance reflects data dispersion, the resulting weights maximize data differences. Using calculation results as observed variables for each indicator and solving the above equations yields variance explanation degrees of 0.465, 0.232, 0.046, 0.216, and 0.041 for degree centrality, betweenness centrality, closeness centrality, K-core value, and core-periphery value respectively. This forms the basis for pairwise importance judgments to construct judgment matrices.

5.1.1 Judgment Matrix Construction and Consistency Test A judgment matrix assesses relative importance between indicators for the upper-level criterion. Based on variance explanation degrees, we conducted pairwise importance comparisons to construct judgment matrices. Importance criteria follow Table 5 . We constructed goal-criterion layer judgment matrices (Table 6) and criterion-scheme layer matrices (Tables 7 and 8).

The random consistency ratio is calculated as $CR = \frac{CI}{RI}$, where $\lambda_{\max}$ is the maximum eigenvalue, n is matrix order, and RI is the average random consistency index. Three judgment matrices have consistency ratios of 0, 0, and 0.0036, all below 0.1, satisfying consistency requirements.

5.1.2 Location Core Degree Weight Determination Using Matlab programming based on judgment matrices, we calculated each indicator's weight relative to upper levels, then aggregated sorting weight vectors to obtain comprehensive weights, shown in Table 9 .

The location core degree expression for a single node is:

$$\text{Core Degree} = \sum_{i=1}^{5} w_i \cdot h_i \quad (4)$$

where w_i represents the comprehensive weight of evaluation indicator i, and h_i represents the value of evaluation indicator i.

AHP determined each indicator's specific impact on node position, enabling quantitative position description and creating conditions for subsequent CTR prediction.

5.1.3 Evaluation System Effectiveness Assessment Using comprehensive weights, we quantitatively evaluated hot Official Accounts' positions in the citation reposting network. Ranking results are shown in Table 10 .

Comparing with the WeChat Official Account influence ranking for the same period, 32% of accounts have ranking changes within 5 positions. The influence ranking is weighted by average daily reads and per-article reads without considering node connections. Given that ads can disseminate through relationships in citation networks, isolated nodes with large fan bases may rank high in influence lists but have poor actual ad delivery. Our social network analysis-based evaluation system comprehensively considers node positions in both whole network and local subnets, predicting CTR closer to actual delivery effectiveness.

5.2 Advertising CTR Prediction

Using AHP-derived position factor weights combined with the CTR prediction model, we used Matlab to predict each account's CTR, with results shown in Table 11 .

5.2.1 Trend Analysis Fitting the scatter points yields the predicted CTR curve shown in Figure 5 [Figure 5: see original paper].

Analysis reveals periodic fluctuating growth in predicted CTR. In the article reposting network, there are 8 fluctuation cycles. Within each cycle, peak and lowest points differ significantly, reflecting the network's locally high clustering

characteristics. Each fluctuation cycle represents a community where core nodes enjoy high predicted CTR while peripheral nodes have low predicted CTR, explaining the fluctuating growth pattern.

5.2.2 Community Analysis Using R language and random walk algorithms, we divided densely connected nodes into communities. The community partition results are shown in Figure 6 [Figure 6: see original paper].

The network divides into 8 communities, with categories 4, 6, and 8 having fewer nodes and others more evenly distributed. In the reposting network, accounts within the same community frequently repost articles, show high mutual attention, and share similar content from the same core nodes, forming regional citation networks. Therefore, the same ad should be avoided across accounts in the same community.

Each community forms a local article reposting network with both core and peripheral nodes. Core nodes have higher predicted CTR, while peripheral nodes have lower predicted CTR. Ad delivery should favor core nodes within communities. Ad delivery effectiveness is significantly influenced by account positions in local subnets, indicating micro-position impacts predicted CTR more than macro-position.

5.2.3 Peak Analysis The predicted CTR trend shows multiple peaks, with People's Daily reaching the maximum of 0.96. Other local peaks stabilize between 0.3-0.7, indicating that in specific local subnets, People's Daily has extremely tight connections with surrounding nodes and absolute positional advantage. Other peaks lack such strong connections, occupying only relatively core positions in local subnets.

For ad delivery, peak points should be prioritized in this order: People's Daily, Xinhua News Agency, Zhanhao, Ten O'Clock Reading, China Search, Visual Magazine, and Global Times. Time-sensitive ads should be placed at high-CTR peak points. Ads placed at high-CTR points leverage positional advantages to disseminate widely within local networks, rapidly achieving delivery effectiveness.

5.2.4 Downturn Analysis We define local minimum points in the predicted CTR trend as downturn points. Figure 5 shows multiple downturn points with clear stratification. Cold Rabbit, Cold Jokes Selection, and Cold Jokes have predicted CTR around 0.2, while other downturn points stabilize around 0.03, extremely low values. This indicates that in the first three communities, nodes are tightly connected, so even relatively peripheral nodes maintain close ties with community members.

Downturn points should be avoided in ad delivery as they hold disadvantaged positions in local subnets. Ads placed at these nodes receive few clicks, meaning

few users learn about the ad content. Communication effectiveness cannot be achieved, and user behavior remains unaffected.

6 Conclusion

This study examines WeChat Official Accounts, investigating precise ad delivery based on CTR prediction. We comprehensively consider both micro-position and macro-position of Official Accounts in social networks, proposing peak and downturn point strategies within communities to improve predicted CTR and ad delivery effectiveness. Our research yields the following conclusions:

(1) Ad delivery should incorporate node positions in social networks. Node positions affect advertising CTR and thus delivery effectiveness. Core-position nodes can expand ad information reach. Increase ad placement on core nodes to maximize diffusion with minimal resources; reduce placement on peripheral nodes with less positional advantage.

(2) In Official Account citation networks, predicted CTR shows periodic fluctuating growth. Each fluctuation cycle represents a community where core nodes enjoy high predicted CTR while peripheral nodes have low predicted CTR, creating large differences.

(3) For nodes within the same community, close interconnections mean ads placed on some nodes will diffuse throughout the community, so placements should be diversified across communities to avoid redundancy and achieve broad, rapid diffusion.

(4) Ad delivery should focus on peak points with high predicted CTR where ads are most likely to be clicked. Downturn points with extremely low predicted CTR should be avoided as they generate few clicks and fail to achieve communication objectives.

(5) Official Account positions are primarily influenced by degree centrality, betweenness centrality, and K-core values. Using account position to predict CTR provides a quantitative reference for ad delivery. Ads placed on accounts with high predicted CTR rankings are most likely to be clicked, achieving communication and media effectiveness.

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Note: Figure translations are in progress. See original paper for figures.