A Comprehensive Investigation of the Advancements for the Computational Advertising Research

Zihang Zhang[a]
School of Accounting, Zhongnan University of Economics and Law, Donghu High-tech Zone, Wuhan, China

Keywords: Computational Advertising, Digital Era, Data-Driven.

Abstract: In the contemporary digital landscape, Computational Advertising (CA) has ascended as a pivotal paradigm, harnessing the power of data and algorithms to orchestrate highly targeted and personalized advertising campaigns. This scholarly article offers a comprehensive analysis of the current state of CA, interrogating its foundational theoretical frameworks, examining practical applications, and delineating the most recent advancements in academic research. The study underscores the amalgamation of multidisciplinary methodologies, with a particular emphasis on real-time bidding mechanisms, sophisticated personalized advertising technologies, and the strategic employment of big data analytics and user profiling for optimized ad delivery. The article critically engages with the ethical implications of CA's rapid proliferation, highlighting concerns surrounding user privacy and data security. In light of these challenges, the research proposes future directions that seek to harmonize technological innovation with the protection of consumer rights, thereby fostering the sustainable evolution of the advertising industry. Through an academic lens, this article scrutinizes the intricate interplay between technological advancements, ethical considerations, and the evolving dynamics of consumer engagement, contributing to the ongoing discourse within the field and shaping future research trajectories.

1 INTRODUCTION

With the advent of the digital era, Computational Advertising (CA) has become an integral component of the advertising industry. This data and algorithm-driven approach to advertising has revolutionized the way brands connect with their audience by enabling highly targeted and personalized messaging. However, the rapid evolution of Computational Advertising has also given rise to a myriad of ethical risks and challenges. These concerns not only threaten consumer privacy and data security but also pose significant questions regarding the sustainable development of the advertising domain.

The digital era has ushered in a transformative phase in the field of advertising, with computational advertising emerging as a key driver of innovation. In their seminal article (Helberger et al., 2020). Jisu Huh and colleagues offer a definitive guide that outlines the theoretical foundations and practical usage within this evolving field. This paper methodically introduces the idea of computational advertising, showcasing it as a technology-focused strategy using advanced algorithms and computing capabilities to boost the effectiveness of advertising tactics.

Huh and Malthouse laid the groundwork with a definition that succinctly captures the core of CA (Huh et al., 2020), subsequently documenting their development from the initial phase of mail-order systems to the modern digital landscape marked by the advent of big data and artificial intelligence. The evolution of this historical context is crucial to fully understand CA's present condition, a cornerstone in advertising where it allows for immediate targeting and customization across various forms of media.

The document also clarifies the future by forecasting forthcoming challenges and opportunities for CA. The draft creates a future-oriented and empirically-based research agenda about safety for consumers, competitive equity, and ethical technology use, and this proves that pro-innovation policies must be nurtured. (Huh et al., 2020).

The article lays a foundation for such studies by assessing current situation in the field of CA research and determining its effects on publications and academic practices in general. This article is a

[a] https://orcid.org/0009-0000-4113-4468

Zhang, Z.
A Comprehensive Investigation of the Advancements for the Computational Advertising Research.
DOI: 10.5220/0013230400004568
In *Proceedings of the 1st International Conference on E-commerce and Artificial Intelligence (ECAI 2024)*, pages 350-354
ISBN: 978-989-758-726-9

thorough literature review, pointing out a few promising possibilities and research tracks which should be taken into consideration in future investigations. The paper demonstrates the CA concept so well by providing fresh ideas in terms of cross-disciplinary research, on strategic advertising, and on transforming the brand's relationship with its audience. Marketing specifically in the digital realm within the last decade is becoming an increasing topic of interest and merits careful scrutiny to provide current discussions within the academic community.

2 METHOD

As the online ad research reaches new heights, the provocative techniques from various disciplines have been fused to examine the complexity of the computational advertising. Informed by the latest findings, the current research trend is moving into a more all-round and multidisciplinary direction. The core computational advertising activity is the discovery of effective ads suited for a certain person in a defined surrounding. The journey requires the unity of many domains in which a search, text analysis, information retrieval, statistical modeling, machine learning, categorization protocols, optimization topics, and microeconomic perspectives are involved.

In the past few years, computational advertising research has seen dynamic development with some main topics being real-time bidding (RTB) adopted effectively, heterogeneous ad technologies developed, and big data and user profiling for accurate ad targeting deployed. The development goes beyond simple algorithm improvement to include consonance with ad logos, studying the role of tech solutions to increase effectiveness of coordinated marketing strategies as well as effective personalization across all customer touchpoints.

2.1 Real-Time Bidding (RTB)

Real-Time Bidding stands as a significant advancement in the realms of display and mobile ads in recent times. RTB enables the accurate targeting of users according to their habits and choices via an immediate auction process, thus improving both the efficiency and the conversion rates of advertisements. This method, which relies on data and behavior for advertising dissemination, offers a more tailored and effective strategy than conventional keyword or content matching techniques (Wang et al., 2016). RTB has radically transformed digital marketing, offering fresh avenues for research in automation, integration, and optimization (Wang et al., 2015). Recent algorithmic frameworks in RTB are chiefly oriented towards these areas:

2.1.1 The Integration of Deep Learning and Reinforcement Learning

In 2023, a study suggested a unique strategy that integrates deep learning with reinforcement learning methods to enhance the effectiveness and precision of RTB. The technique utilizes deep neural networks for forecasting auction specifics and market costs, and reinforcement learning algorithms ascertain the ideal bid price (Sharma, 2023).

2.1.2 Statistical Arbitrage Mining (SAM)

In 2015, research unveiled SAMer, a meta-bidder employing statistical arbitrage to optimize anticipated net gains. SAMer pursues the best bids by enhancing feature optimization and utilizes traditional data-driven learning techniques to evaluate prospective income and expenses (Zhang et al., 2015).

2.1.3 Conversion Rate Prediction Methods Combining Regression and Triplet Learning

A 2018 study suggested a method (CRT) combining regression loss and triplet ranking loss, targeting precise ranking figures and accurate regression calculations to refine buyer conversion rate forecasts in RTB (Shan et al., 2018).

2.1.4 SKOTT Optimization Layer

In 2018, research unveiled SKOTT, an algorithm aimed at enhancing specific key performance indicators (KPIs). This is achieved by efficiently setting up DSPs and encouraging them to compete with one another. SKOTT, a sophisticated iterative algorithm reliant on gradient descent, tackles challenges like budget distribution, calculating anticipated average bids, and averting underdelivery.

2.2 Machine Learning and Statistical Models

Analytics models based on machine learning have become an integral aspect of this computational advertising domain. Examining past patterns of data, models may be trained to predict user behavior under certain advertisement conditions. Thus, selection of ads is made better, and they are distributed through better methods. The Deep Image CTR Model (DICM) includes the characteristics of the image content that impacts the user behavior and the advertisement creativity to engage users.(Ge et al., 2017).

To enhance ad distribution's efficiency and effectiveness, the immediate assessment and fine-tuning of advertisements are also crucial. The process encompasses applying statistical feature analysis techniques to gather statistical data and regression analysis for the advertisement's specific placement effectiveness, coupled with big data management systems for managing crowds and computing profiles, aiming to tailor advertisement placements to meet real business requirements (Wang et al., 2021).

Regarding the training and enhancement methods for forecasting user reactions to certain adverts in computational advertising studies, these usually encompass several stages.

2.2.1 Data Collection and Preprocessing

Initially, an extensive collection of data on user behavior and advertising characteristics is required. Such information could encompass the click patterns, buying patterns, and browsing patterns of users. Moreover, techniques for recognizing sentiments are applicable in analyzing how the ad content emotionally responds, like the attributes Convolutional Neural Networks (CNNs) identify to capture the emotional essence in advertisements (Gharibshah et al., 2021).

2.2.2 Feature Engineering

After data preprocessing, the next stage is the feature engineering. This step involves extracting useful information from the raw data in order to construct features that can represent users' responses to advertisements. For example, deep learning models such as Convolutional Neural Networks (CNN) and Long Short-Term Memory Networks (LSTM) can be used to automatically extract and learn these features.

2.2.3 Model Selection and Training

Choosing a suitable machine learning model is the next imperative step. Popularly employed methods for supervised learning include logistic regression, support vector machines, decision trees, random forests, and convolutional deep learning. For unsupervised learning, long short-term memory networks can also be mentioned. Such models should be trained with historical data to be able to make predictions about the possible responses of a user to certain advertisements.

2.2.4 Model Optimization and Validation

After finalizing the training phase, it's necessary to evaluate and validate the models using fresh datasets to determine their forecast accuracy. This process usually includes methods like cross-validation to guarantee the model's capacity for generalization. Furthermore, techniques like A/B testing serve as tools for assessing various advertising tactics in real-time scenarios.

2.2.5 Real-time Applications and Feedback Loops

Practically, it's imperative for machine learning models to handle live data and persistently modify their forecasts in response to novel inputs. Such a model must be capable of being flexible and adaptable to sustain its effectiveness amidst evolving market dynamics (Rajan, 2018).

3 DISCUSSIONS

3.1 Limitations and Challenges in the Field

Although significant progress has been made, there are still some limitations and challenges in this field.

3.1.1 Explainability

In computational advertising, the algorithms are often so intricate that they are not comprehensible. This is the root cause of opacity in the decision-making process supported by those algorithms. To this end, this lack of transparency not only destabilizes the trust of advertisers but also makes it difficult for consumers to perceive the reason why they are presented with specific ads.

3.1.2 Applicability

Research and applications of computational advertising are often highly dependent on the quality and availability of data. However, issues such as privacy leakage and data bias may arise during data collection and processing, which can limit the applicability and effectiveness of computational advertising techniques (Gao et al., 2023).

3.1.3 Privacy

The collection and use of user data is inevitable in computational advertising. However, it also raises significant concerns about user privacy protection.

How to protect user privacy while improving advertising effectiveness has become an urgent issue. (Helberger et al., 2020).

3.2 Future Prospects

Some several possible solutions can be considered in this case to solve the limitations and challenges mentioned above.

3.2.1 Adoption of a User-centered Design Framework

According to the study carried out by (Hosain et al., 2023), the development of transparent and interpretable AI systems requires interdisciplinary collaboration, including computer science, artificial intelligence, ethics, law, and social sciences. The design should be user-centered to ensure that the system is not only technically feasible but also socially and ethically acceptable.

3.2.2 Adopt a User-centered Design Framework

Scott M proposed the SHapley Additive exPlanations (SHAP) framework (Lundberg et al., 2017), a unified approach to interpreting the predictions of complex models. By assigning importance values to each feature, SHAP helps users understand the model's decision-making process, which improves the transparency and interpretability of the model.

3.2.3 Maintenance of Localized User Profiles for Devices

Traditional recommender systems rely on server-side large-scale vector computation, which is not only inefficient but also may compromise user privacy. A new approach is to store user profiles entirely on the user's device and obtain appropriate recommendations from web portals in an encrypted way, which can effectively protect user privacy (Tulabandhula et al., 2017).

3.2.4 Adoption of K-anonymization Techniques

K-Anonymity is a data protection model that ensures that each individual's information cannot be individually distinguished from the anonymized dataset (Sweeney, 2002). This approach effectively minimizes the risk of personal information leakage while allowing advertising systems to continue to use this data for effective user targeting.

4 CONCLUSIONS

Computational advertising has turned into the main player in the digital generation, which governs by data and algorithms to target more precisely the needed audience. But it also runs into ethical matters such as privacy and security of data. Research has crossed boundaries with - especially - use of interdisciplinary methods like real-time bidding and machine learning, which increased advertisement efficacy and performance. Yet, there are still various problems, namely algorithm opacity and data privacy. In the future, we will specifically cultivate explainable algorithms, data privacy protection, and intelligent advertisements. It hopes to come up with a unique development pattern that balances technological innovation with consumer privacy rights.

REFERENCES

Gao, B., Wang, Y., Xie, H., Hu, Y., & Hu, Y. 2023. Artificial Intelligence in Advertising: Advancements, Challenges, and Ethical Considerations in Targeting, Personalization, Content Creation, and Ad Optimization. Sage Open, 13(4).

Ge, T., & Wu, X. 2021. Accurate Delivery of Online Advertising and the Evaluation of Advertising Effect Based on Big Data Technology. Mobile Information Systems, 2021, 1-10.

Gharibshah, Z., & Zhu, X. 2021. User response prediction in online advertising. arXiv.

Helberger, N., Huh, J., Milne, G., Strycharz, J., & Sundaram, H. 2020. Macro and Exogenous Factors in Computational Advertising: Key Issues and New Research Directions. Journal of Advertising, 49(4), 377–393.

Hosain, Md. T., Anik, M. H., Rafi, S., Tabassum, R., INSİA, K., & SIDDIKY, Md. 2023. Path To Gain Functional Transparency In Artificial Intelligence With Meaningful Explainability. Journal of Metaverse, 3, 166-180.

Huh, J., & Malthouse, E. C. 2020. Advancing Computational Advertising: Conceptualization of the Field and Future Directions. Journal of Advertising, 49(4), 367–376.

Latanya Sweeney. 2002. K-anonymity: a model for protecting privacy. Int. J. Uncertain. Fuzziness Knowl.-Based Syst., 10(5), 557–570.

Lundberg, S., & Lee, S.-I. 2017. A Unified Approach to Interpreting Model Predictions. ArXiv.org.

Sharma, P. 2023. Improving Real-Time Bidding in Online Advertising using Markov Decision Processes and Machine Learning Techniques. International Journal of Advanced Engineering and Nano Technology, 10(7), 1–8.

Suju Rajan. 2018. Computational Advertising at Scale. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (KDD '18), 2875.

Tulabandhula, T., Vaya, S., & Dhar, A. 2017. Privacy-preserving Targeted Advertising. Journal of Business Analytics, 3.

Wang, J., & Yuan, S. 2015. Real-Time Bidding: A New Frontier of Computational Advertising Research. Proceedings of the Eighth ACM International Conference on Web Search and Data Mining.

Wang, J., Zhang, W., & Yuan, S. 2016. Display Advertising with Real-Time Bidding (RTB) and Behavioural Targeting. arXiv.

Zhang, W., & Wang, J. 2015. Statistical Arbitrage Mining for Display Advertising. In Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD '15), 1465–1474.