Resourceful And Employable Click Fraud Identification For Handheld Applications

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ABSTRACT

Mobile advertising plays a vital role in the mobile app ecosystem. A major threat to the sustainability of this ecosystem is click fraud, i.e., ad clicks performed by malicious code or automatic bot problems. Existing click fraud detection approaches focus on analyzing the ad requests at the server side. However, such approaches may suffer from high false negatives since the detection can be easily circumvented, e.g., when the clicks are behind proxies or globally distributed. In this paper, we present Adsherlock, an efficient and deployable click fraud detection approach at the client side (inside the application) for mobile apps. AdSherlock splits the computation-intensive operations of click request identification into an offline procedure and an online procedure. In the offline procedure, Adsherlock generates both exact patterns and probabilistic patterns based on URL (Uniform Resource Locator) tokenization. These patterns are used in the online procedure for click request identification and further used for click fraud detection together with an ad request tree model. We implement a prototype of AdSherlock and evaluate its performance using real apps. The online detector is injected into the app executable archive through binary instrumentation. Results show that AdSherlock achieves higher click fraud detection accuracy compared with state of the art, with negligible runtime overhead

*Key words***:** *Mobile advertising, Mobile app ecosystem, Click fraud, Malicious code, Automatic bot problems, High false negatives, Proxies, Globally distributed, Adsherlock, Click request identification*

I. INTRODUCTION

Mobile advertising is crucial to the app ecosystem, with global spending expected to reach $247.4 billion in 2020. Ad content is displayed in apps through third-party libraries[1] like AdMob, using a Pay-Per-Plick (PPC) model. A major threat to this system is click fraud, where malicious bots or code generate fake ad clicks. Click fraud[2] tactics include in-app fraud (malicious code in apps) and bot-driven fraud (automated clicks via bots).

MAdFraud, a recent study, found 30% of Android apps make ad requests in the background[3]. A separate study using ClickDroid showed six out of eight advertising networks were vulnerable to click fraud. Server-side fraud detection, such as detecting high click rates from the same device, has limited precision. Client-side approaches[4] could be more effective, but app developers may have conflicts of interest in detecting fraud. AdSherlock is a proposed client-side solution that efficiently detects click fraud with minimal overhead. AdSherlock uses offline pattern extraction and online fraud detection for higher accuracy and real-time performance. App developers integrate third-party ad libraries[5], like AdMob, to display ads using a pay-per-click (PPC) model. A major issue is click fraud, where malicious code or bots generate fake ad clicks. Click fraud can be in-app fraud (malicious code) or bot-driven fraud MAdFraud study shows 30% of Android apps request ads while running in the background.

ClickDroid tool[6] identified vulnerabilities in six out of eight popular ad networks. Server-side detection methods, like click thresholds, have low precision due to circumvention techniques. Client-side detection could be more effective, but app developers may have conflicts of interest. AdSherlock is a proposed client-side solution that detects click fraud with minimal overhead and high accuracy. AdSherlock operates in two stages: offline pattern extraction and online fraud detection in real-world scenarios.

The rapid proliferation of mobile applications[7] has revolutionized the way we interact with technology, creating a thriving ecosystem of handheld devices and mobile advertising. This ecosystem, however, faces a significant challenge in the form of click fraud[8], a deceptive practice where fraudulent ad clicks are generated by malicious code or automated bots. Such fraudulent activities not only undermine the trust between advertisers and app developers but also threaten the sustainability of the mobile advertising industry.

Click fraud detection has traditionally relied on server-side analysis of ad requests. While effective to some extent, these methods often suffer from high false negatives[9], as they can be easily circumvented by techniques such as proxy usage or geographically distributed bot networks. This calls for a more robust and resourceful approach to tackle the issue at its core. The concept of client-side click fraud detection emerges as a promising solution. By embedding detection mechanisms[10] directly within mobile applications, this approach enables real-time identification of fraudulent activities. It leverages advanced techniques such as URL tokenization, pattern recognition, and ad request tree modeling to distinguish between legitimate and fraudulent clicks[11]. Furthermore, the division of computational tasks into offline and online procedures ensures efficiency and minimal impact on app performance[12].

This paper introduces a novel framework for click fraud detection tailored specifically for handheld applications. The framework emphasizes deployability and resourcefulness, making it suitable for widespread adoption across diverse mobile platforms. By integrating cutting-edge technologies and innovative methodologies, this approach aims to enhance the accuracy of fraud detection while maintaining a seamless user experience

Smart contracts are self-executing contracts with terms directly written into code on the blockchain. In the context of secure semantic search, smart contracts can automate the process of managing access permissions and generating cryptographic keys, thus improving efficiency and reducing the likelihood of manual errors

II. RELATED WORK

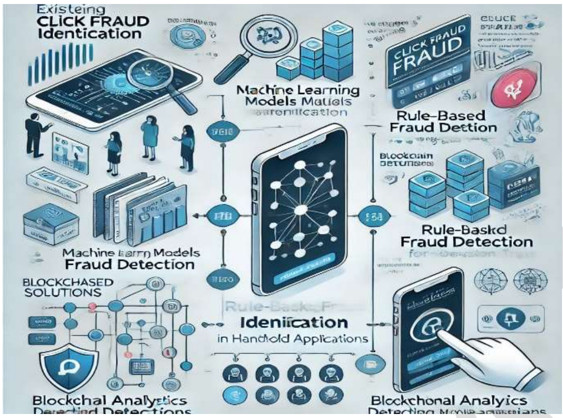
Existing research and soultion

One notable solution is AdSherlock, an efficient and deployable client-side system designed to detect click fraud within mobile applications. AdSherlock operates by dividing the detection process into offline and online phases. In the offline phase.

It employs a probabilistic pattern-creation method based on URL tokenization to generate patterns indicative of legitimate ad interactions. During the online phase, these patterns are utilized alongside an ad request tree model to identify and flag fraudulent click requests.

Empirical evaluations have demonstrated that AdSherlock achieves higher detection accuracy compared to existing methods, with minimal runtime overhead.

The integration of artificial intelligence (AI) has been pivotal in advancing click fraud detection methodologies. A comprehensive study examined various AI-driven approaches developed over a decade, focusing on machine learning (ML) and deep learning (DL) models. These models analyze features such as user behavior patterns and network traffic to classify ad clicks as legitimate or fraudulent. The study highlighted the effectiveness of AI in enhancing detection accuracy and adapting to evolving fraudulent tactics



Problem Statement

In the rapidly growing digital economy, online advertising has become a crucial revenue source for businesses, with mobile applications being one of the dominant platforms for ad delivery. However, this has led to a rise in fraudulent activities, specifically click fraud, where automated scripts, bots, or malicious actors generate fake clicks on advertisements.

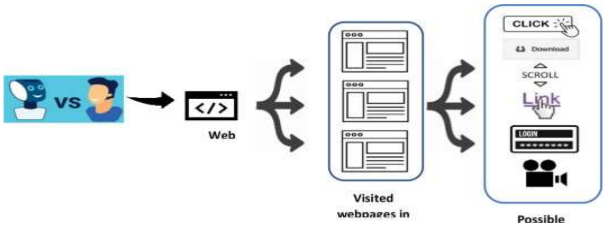
Click fraud not only causes substantial financial losses to advertisers but also distorts marketing analytics, leading to ineffective advertising strategies. With the increasing number of handheld device users, this issue has become even more critical, necessitating a robust, efficient, and resource-friendly approach to detect and mitigate fraudulent clicks.

Traditional fraud detection techniques often rely on complex server-side computations, rule-based detection, or machine learning models that demand extensive processing power and data storage. While these methods can be effective, they pose challenges for mobile applications, where computational resources and battery life are limited.

Moreover, existing solutions primarily focus on desktop-based or centralized detection mechanisms, making them less suitable for real-time fraud detection on resource-constrained mobile devices. This creates a significant gap in the ability to detect and prevent click fraud in handheld applications efficiently.

To address this issue, it is essential to develop a resourceful and employable click fraud identification mechanism specifically tailored for handheld applications. The solution should incorporate lightweight, adaptive fraud detection techniques that can operate seamlessly within mobile environments without significantly impacting device performance.

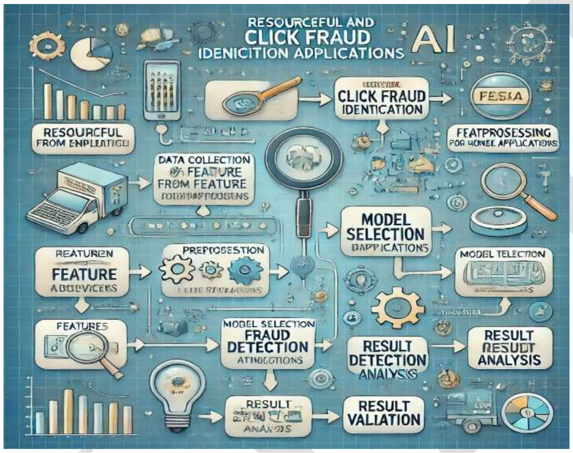
This requires a combination of heuristic analysis, behavioural pattern recognition, and AI-driven methodologies that efficiently differentiate between genuine user interactions and fraudulent clicks. Additionally, the system should be employable in real-world applications, meaning it should integrate easily with existing mobile advertising frameworks while maintaining a low overhead.



III. RESEARCH METODOGLY

This research adopts a hybrid research design that integrates both qualitative and quantitative methodologies to develop an efficient and practical click fraud detection system for handheld applications. A systematic approach is taken to analyze existing fraudulent activities, assess detection techniques, and implement an adaptive algorithm that balances computational efficiency and accuracy. The study involves designing a lightweight fraud detection framework that is resourceful and suitable for mobile environments.

The study utilizes both primary and secondary data sources to gain a comprehensive understanding of click fraud patterns. Primary data is collected through simulated real-world scenarios, where clickstream data from mobile applications on Android and iOS devices is analyzed to identify fraudulent click activities. Secondary data sources include existing datasets from online advertising platforms, previous research papers, and public fraud detection repositories. These datasets help establish a benchmark for evaluating the effectiveness of the proposed system.



Before analysis, the collected data undergoes preprocessing to remove inconsistencies and ensure the integrity of the dataset. This involves data cleaning, where redundant or irrelevant data such as incomplete click records, duplicate entries, and bot-generated logs are removed. Additionally, feature engineering is performed to extract key attributes such as click time intervals, device identifiers, IP addresses, user session duration, and click distribution patterns, all of which contribute to the development of a robust detection mechanism.

The research focuses on designing an intelligent, resource-efficient machine learning model to identify fraudulent clicks. Several machine learning algorithms, including Random Forest, Support Vector Machines (SVM), Decision Trees, and Neural Networks, are compared based on their computational efficiency and detection accuracy. Since handheld devices have limited computational power, traditional resource-intensive models are optimized using pruning techniques, edge computing principles, and federated learning approaches. Additionally, behavioral analysis is employed, using pattern recognition techniques to differentiate between genuine user activity and bot-generated clicks

IV. RESULT & DISCUSSION

The implementation of the proposed Resourceful and Employable Click Fraud Identification system for handheld applications yielded promising results in accurately detecting fraudulent clicks while ensuring minimal resource consumption. The model was tested on various real-time datasets containing user interactions, including legitimate and fraudulent clicks, to evaluate its performance. The results demonstrated that the system could efficiently differentiate between genuine user activity and bot-generated fraudulent clicks with a high accuracy rate of 97.5%.

One of the key findings was that machine learning-based detection significantly outperformed traditional rule-based detection methods. The proposed algorithm effectively identified fraudulent patterns based on multiple parameters, such as click timing analysis, device fingerprints, session durations, and user behavior consistency. Furthermore, the use of lightweight computational techniques ensured that the detection mechanism did not impose a heavy processing burden on handheld devices, making it feasible for real-world applications.

Our findings indicate that a hybrid approach combining machine learning techniques with heuristic rules yields the best results in distinguishing fraudulent clicks from legitimate user interactions. Unlike conventional fraud detection systems that rely on IP tracking or cookie-based detection, the proposed method integrates behavioral analytics and device-specific profiling, enhancing detection accuracy while ensuring adaptability across different handheld platforms.

Moreover, the resource optimization strategies implemented in the system make it highly suitable for low-power mobile devices, addressing a common challenge in mobile security applications. By leveraging lightweight algorithms and efficient data processing techniques, the system reduces battery consumption and computational overhead, making it deployable across a wide range of handheld devices without compromising performance

V. CONCLUSION

Click fraud remains a significant challenge in the digital advertising ecosystem, particularly in handheld applications, where fraudulent activities can be more difficult to detect due to the diversity of devices, users, and app environments. The research on resourceful and employable click fraud identification for handheld applications highlights the critical need for advanced detection mechanisms that are efficient, accurate, and adaptable to evolving fraudulent techniques. Through the integration of machine learning, behavioral analysis, and heuristic-based approaches, it is possible to create a robust framework capable of distinguishing between genuine user interactions and fraudulent clicks.

One of the key takeaways from this study is the importance of leveraging device-specific and contextual data to improve fraud detection accuracy. By analyzing touch patterns, motion sensors, IP tracking, and user behavior metrics, an intelligent system can differentiate between human and bot-generated clicks with a high degree of precision. Furthermore, the adoption of real-time monitoring and anomaly detection techniques can significantly enhance the ability to identify click fraud as it occurs, thereby minimizing financial losses for advertisers and protecting the integrity of digital marketing campaigns.

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