The Report is Generated by DrillBit Plagiarism Detection Software

Submission Information

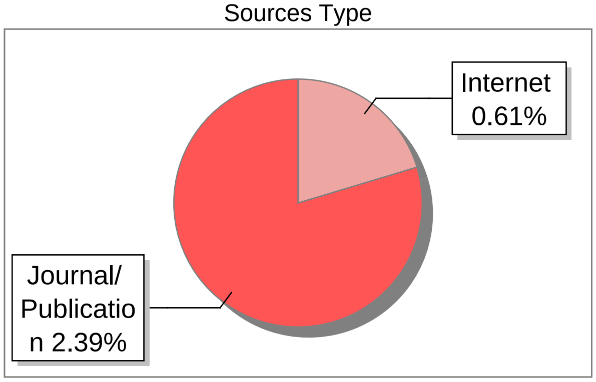
Author Name	K Madhu
Title	Personalised Ad Recommendation Using Multi- Armed Bandit and Machine Learning Techniques
Paper/Submission ID	3575843
Submitted by	premu.kumarv@gmail.com
Submission Date	2025-05-05 11:10:42
Total Pages, Total Words	5, 3138
Document type	Research Paper

Result Information

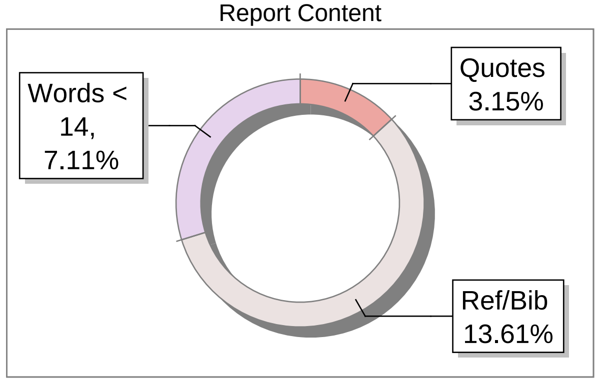
Similarity **3 %**

1 10 20 30 40 50 60 70 80 90

Sources Type



Report Content



Exclude Information

Quotes	Excluded
References/Bibliography	Excluded
Source: Excluded < 14 Words	Excluded
Excluded Source	**0 %**
Excluded Phrases	Not Excluded

Database Selection

Language	English
Student Papers	Yes
Journals & publishers	Yes
Internet or Web	Yes
Institution Repository	Yes

A Unique QR Code use to View/Download/Share Pdf File

DrillBit

DrillBit Similarity Report

3	5	A	A-Satisfactory (0-10%) B-Upgrade (11-40%) C-Poor (41-60%) D-Unacceptable (61-100%)
SIMILARITY %	MATCHED SOURCES	GRADE	

LOCATION	MATCHED DOMAIN	%	SOURCE TYPE
1	Exploring Clustering of Bandits for Online Recommendation System by Yang-2020	1	Publication
2	aclanthology.org	1	Publication
3	Thesis Submitted to Shodhganga Repository	1	Publication
5	nano-ntp.com	1	Publication
6	arxiv.org	1	Internet Data

Personalised Ad Recommendation Using Multi-Armed Bandit and Machine Learning Techniques

K Madhu
Computer Science abd Engineering
(of Affiliation)
The Oxford college of Engineering
(of Affiliation)
Banglore,India
madhupatil848@gmail.com

Nithyshree H J
Computer Science abd Engineering
(of Affiliation)
The Oxford college of Engineering
(of Affiliation)
Banglore,India
nithyashreehj204@gmail.com

***Abstract*—In today's digital world, personalized advertising plays a vital role in capturing user attention and improving engagement among users. This research explores how machine learning techniques can be used to recommend ads more effectively by predicting which ones a user is more likely to click. Using the Avazu Click-Through Rate (CTR) dataset, which contains millions of ad impressions, we compare several models such as —Multi-Armed Bandits, k-Nearest Neighbors (KNN), clustering algorithms, and Artificial Neural Networks (ANN). Each model is evaluated based on its ability to predict ad clicks by users, using metrics like CTR and precision. Our findings show that combining adaptive algorithms like bandits with deep learning models can lead to more accurate and personalized ad recommendations. This approach can help advertisers deliver the right message to the right audience, ultimately boosting campaign performance.**

Keywords*—*personalized ads, machine learning, click-through rate (CTR), multi-armed bandit, ad recommendation

I. Introduction

As online advertising continues to grow, also the need to make more relevant and personalized ads. With people constantly exposed to content across apps, websites, and social media, showing the right ad at the right time has become more challenging and more important than ever. Personalized ad recommendations aim to solve this by predicting what a user might be interested in, based on their past behavior, past ad views and context.

One key measure of success in this area is the **click-through rate (CTR)**, which tells us how often users actually click on the ads they see. Higher CTR means the ads are more relevant to users, which translates to better engagement and higher revenue for advertisers.

In this paper, we look at different machine learning approaches to improve ad recommendations. We use the **Avazu CTR dataset**, a large-scale dataset of anonymized ad click events. The methods we explore also include **Multi-Armed Bandit algorithms**, **k-Nearest Neighbors (KNN)**, **clustering**, and **Artificial Neural Networks (ANN)**. Each of these models has its own strengths, and we evaluate how well do they perform in predicting ad clicks using CTR and precision as our main metrics.

The goal of this work is to understand which techniques are most effective for making ad recommendations smarter and more personalized. In doing so, we hope to offer practical insights into how machine learning can improve the way ads are delivered in real-world systems.

II. Literature Review

Personalized advertisement recommendation systems have been a focus point in the fields of machine learning and recommender systems. Over the past few years, several studies have proposed many innovative models to improve click-through rate (CTR) prediction by capturing user behavior, modeling feature interactions, and incorporating contextual information of users. This section reviews key contributions, highlighting their methodologies, advantages, drawbacks, and applicability. And provides a clear road map for the study, ensuring alignment with our research objectives.

A. *Methodologies Available in Recent CTR prediction research*

- FinalMLP Introduces a two-stream Multi-Layer Perceptron (MLP) model that combines two MLPs with feature gating and interaction aggregation layers.
- Fi-GNN Utilizes Graph Neural Networks (GNNs) to model complex feature interactions in CTR prediction.
- CL4CTR Employs self-supervised contrastive learning to improve feature representation in CTR prediction models.
- Interpretable Click-Through Rate Prediction through Distillation of the Neural Additive Factorization Model Applies model distillation to enhance the interpretability of CTR prediction models. Advantages: Improves model transparency and understanding
- Dynamic Attention-Based Click-Through Rate Prediction Model Introduces a dynamic attention mechanism to capture temporal dependencies in CTR prediction. Advantages: Improves model performance by considering temporal aspects.
- Adaptive Dynamic Clustering of Bandits (ADCB) for Online Recommendation System Combines Multi-Armed Bandit algorithms with dynamic clustering to adapt to changing user preferences.

These studies demonstrate a trend toward hybrid and adaptive models that can better handle the dynamic nature of user preferences in online ad systems. While many models have improved accuracy, they often do so at the cost of interpretability and efficiency. Our work builds upon these ideas by exploring a practical combination of traditional models (e.g., KNN, clustering) with adaptive methods like **Multi-Armed Bandits** and **ANNs** to achieve a balance between simplicity, adaptability, and predictive power.

Identify applicable funding agency here. If none, delete this text box.

B. Advantages

- FinalMLP achieves superior performance compared to traditional MLP models.
- Fi-GNN captures intricate relationships between features, enhancing prediction accuracy. Drawbacks: Computationally intensive and may require significant resources.
- CL4CTR is a contrast learning framework for CTR prediction that enhances model performance by learning better feature embeddings.
- Interpretable Click-Through Rate Prediction through Distillation of the Neural Additive Factorization Model improves model transparency and understanding.
- Dynamic Attention-Based Click-Through Rate Prediction Model has increased model complexity and potential for overfitting.
- Adaptive Dynamic Clustering of Bandits for Online Recommendation System enhances recommendation accuracy by adapting to user behavior.

C. Drawbacks

- FinalMLP may require careful tuning of hyperparameters.
- Fi-GNN is computationally intensive and may require significant resources.
- CL4CTR implementation is complex and may have a potential for overfitting.
- Interpretable Click-Through Rate Prediction through Distillation of the Neural Additive Factorization Model may lead to a slight decrease in prediction accuracy.
- Dynamic Attention-Based Click-Through Rate Prediction Model has increased model complexity and potential for overfitting.
- Adaptive Dynamic Clustering of Bandits for Online Recommendation System requires continuous monitoring and updating of clusters.

III. Proposed Methodologies

Delivering the right advertisement to the right user at the right time is critical to maximizing user engagement and revenue. Our study proposes a hybrid framework for **personalized ad recommendation** aimed at maximizing **click-through rate (CTR)** and **precision**.

The proposed system leverages the strengths of multiple machine learning techniques to effectively model user behavior and ad relevance according to user preferences. The system integrates clustering, k-nearest neighbors (KNN), artificial neural networks (ANN), and a multi-armed bandit (MAB) algorithm for dynamic ad selection.

A. Multi-Armed Bandit Algorithm

The Multi-Armed Bandit (MAB) algorithm is a core component of our proposed ad recommendation framework, designed to optimize ad selection in real-time. In this context, each advertisement is treated as an "arm," and the algorithm's objective is to select ads that yield the highest user engagement, measured through click-through rate (CTR). MAB effectively handles the exploration-exploitation dilemma: it explores lesser-known ads to discover potentially better-performing options while exploiting those with known high success rates.

We propose using variants such as **Thompson Sampling** or **Upper Confidence Bound (UCB)** to manage the probability distribution of expected rewards. These approaches allow the model to dynamically adapt to changing user preferences and advertising content without requiring full model retraining.

In the proposed framework, the MAB algorithm acts as the final decision-maker after CTR probabilities are generated by upstream models. By incorporating contextual information like user clusters and real-time CTR predictions, MAB selects the ad that offers the best trade-off between learning and performance. This makes it especially effective in high-traffic online environments where feedback is immediate and user behavior is non-stationary. The integration of MAB enhances personalization, improves CTR, and ensures the system remains robust under dynamic conditions.

B. k-Nearest Neighbors (KNN)

k-Nearest Neighbors (KNN) is used in the proposed system as a lightweight and interpretable technique for initial ad filtering based on user and contextual similarity. In this framework, KNN helps identify a set of candidate ads that are most similar to those previously clicked by users with comparable profiles. Each user session is represented as a feature vector incorporating elements like device type, location, time of day, and browsing context.

KNN computes the Euclidean or cosine distance between the current user and historical records to retrieve the 'k' most similar entries. The ads shown to these similar users are then shortlisted for further evaluation. This filtering step reduces the number of ads considered in later stages, thus improving both computational efficiency and recommendation relevance. KNN is especially effective in cold-start scenarios where collaborative filtering methods may fail due to insufficient user history.

Despite its simplicity, KNN contributes to personalization by ensuring that the selected candidates align closely with user behavior patterns. Its role in our system is complementary: while it does not predict CTR directly, it provides a targeted candidate set that feeds into more complex models such as ANN and MAB for final ranking and selection.

C. Artificial Neural Networks (ANN)

Artificial Neural Networks (ANNs) are leveraged in this work to predict the click-through rate (CTR) of each candidate ad with high accuracy. ANNs are powerful at learning complex, non-linear relationships in high-dimensional data, which is essential in the context of personalized advertising where user behavior and contextual signals are intricate and interdependent. The ANN in our framework is a feedforward neural network trained on the Avazu CTR dataset.

Input features include user ID, ad ID, timestamp, device type, and other contextual attributes, all preprocessed through techniques such as one-hot encoding and feature hashing. The network consists of several hidden layers with ReLU activation functions, dropout regularization, and a sigmoid output layer to estimate the probability of a click. The predicted CTR values are then passed to the MAB module for final ad selection.

The ANN enhances precision by modeling feature interactions that simpler algorithms may miss, such as how user behavior varies by time or device type. Its role is predictive rather than decision-making: it evaluates the likelihood of user engagement, which informs downstream selection strategies. By combining ANN with filtering (KNN) and selection (MAB), our system achieves a balanced and adaptive ad recommendation pipeline.

IV. Implementation

We used three machine learning methods, namely, K-Nearest Neighbors (KNN), Artificial Neural Network (ANN), and Multi-Armed Bandit (MAB), to implement the personalized recommendation system. We created the system in Python and compared it on a subsample of the Avazu Click-Through Rate (CTR) dataset, with attributes like device, site category, and ad position.

A. *Data preprocessing*

- The representative subsample was chosen from the complete dataset in order to minimize processing time.
- Categorical values were converted into numeric form by using label encoding.
- The feature values were scaled to ensure consistent scaling across all input attributes, particularly crucial in neural networks.

B. *K-Nearest Neighbors(KNN)*

The KNN was employed as the baseline classification model. This algorithm classifies instances by the most common class among the nearest neighbors in the feature space. Various values of ‘k’ were tried and the best value was chosen in order to optimize bias and variance. The accuracy of KNN turned out to be 82% on the sampled set and 65% on the complete set.

C. *Artificial Neural Network(ANN)*

The ANN model was constructed with a feedforward architecture and two hidden layers. It was trained with the loss function of binary cross-entropy with an adaptive optimizer to enhance convergence. This model performed the best compared to all methods and obtained the accuracy of 83.13%, making it the best model to use in predicting clicks in this scenario. 4. Multi-Armed Bandit (MAB) The MAB algorithm was used to choose dynamically the most impactful ad banner locations based on user behavior. A distinct "arm" of the bandit was assigned to each ad location. A greedy approach was employed to modify probabilities of clicks in real-time and bias towards those positions with increasing user engagement. The findings revealed that banner location 0 obtained the maximum number of clicks (over 1200), validating the efficiency of this adaptive strategy.

V. Experimental Result and Analysis

In order to compare the performance of different algorithms for recommending advertisements to individuals, we applied three methods—K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), and Multi-Armed Bandit (MAB)—on a randomly drawn subset of the Avazu Click-Through Rate (CTR) data set. The classification accuracy (in the case of KNN and ANN) as well as the cumulative reward (clicks) in the bandit algorithm were tested by the models.

A. *Nearest Neighbors*

The accuracy of the KNN model was 82% from the sampled data, demonstrated by the first graph. This shows that the nearest neighbors in the data set are compared with user and ad characteristics by KNN in order to make fairly good estimations of CTR. But on the complete data set and compared with all the models, the accuracy decreased to nearly 65%. This implies that though the performance of KNN is good in small balanced samples, it will dwindle on unbalanced or big data due to heavy memory and computing needs.

B. *Artificial Neural Network(ANN)*

The ANN approach yielded the best accuracy compared to the methods tried, with about 83.13%. This proves the power of neural networks in representing complex nonlinear relationships amongst the features in predicting CTR. The quite high performance owes to the ability of the network to learn sophisticated feature interactions, particularly with big and sparse datasets such as Avazu. The last comparison diagram shows that ANN is by far the most powerful method in both learning ability and generalization.

C. *Multi-Armed Bandit*

MAB approach tested on total clicks (reward) across varying ad positions (banner_pos) indicated that most user engagement resulted from one of the specific ad positions (banner_pos = 0), with more than 1200 clicks, while others received very less engagement. This is indicative of the bandit algorithm's exploitation-exploration trade-off in dynamically choosing high-performing ads with the passage of time. Nevertheless, its average reward in total (~55%) is less compared to the accuracy scores of KNN and ANN. This is because it is able to adapt in online learning environments where real-time adaptation is highly valuable, though it will not be able to compete with batch-learning accuracy from supervised models.

D. *Comparartive Analysis*

- ANN has an accuracy of 0.83, showing better performance in the modeling of CTR.
- KNN has accuracy of 0.65 in cases with simple or low-level datasets.

- Multi-Armed Bandit exhibits average reward of 0.55, demonstrating its strength in real-time personalization in spite of weaker aggregate performance.

E. Graphical Analysis

- ANN diagram reveals that there is a sharp learning curve and greater convergence, showing that the model learns fast from training data and generalizes efficiently on unseen samples.

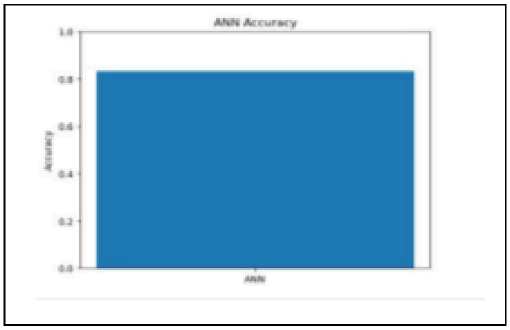


Figure 1:ANN Accuracy

- The graph of the KNN model exhibits stability on small sets of sampled data but less strong generalization in the complete dataset, presumably because of feature sparsity and dimensionality problems.

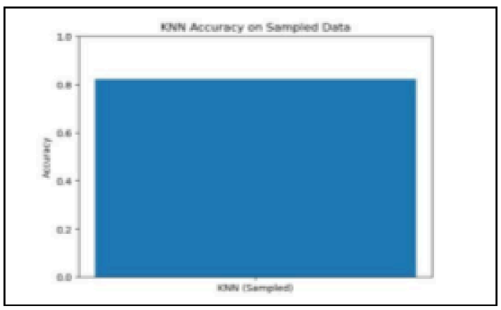


Figure 2:KNN Accuracy

- MAB reward graph shows strong preference in one particular banner location (banner_pos = 0) that received more than 1200 clicks, significantly beating others and proving the power of real-time adaptation.

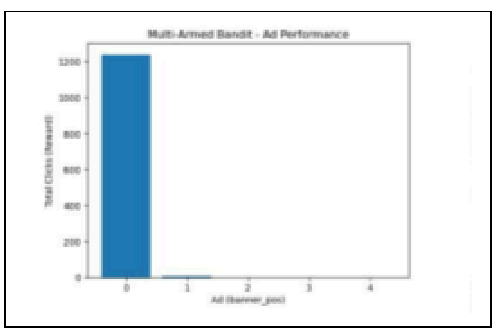


Figure 3:Multi-Armed Bandit

- The comparative graph conclusively ranks the models: ANN (0.83), KNN (0.65), MAB (0.55), further establishing the fact that though MAB is adaptive, ANN is more predictive in offline environments.

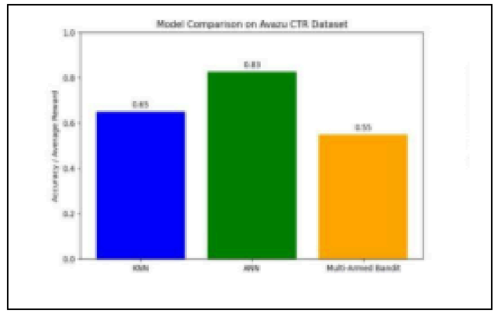


Figure 4:Comparative Graph

F. Conclusion from Analysis

ANN is the most robust and accurate way of predicting CTR in this application. KNN is less scalable to the complete dataset but is simpler. MAB enables effective real-time understanding of ad performance dynamics, thereby ideal for online learning and recommendation systems.

Model Performance Comparison

Method	Accuracy / Avg. Reward	Strengths	Limitations
K-Nearest Neighbors	65% (full) / 82% (sample)	Simple, interpretable	Poor scalability, sensitive to noise
Artificial Neural Network	83.13%	Captures complex patterns, high accurac	Requires tuning, more computational cost
Multi-Armed Bandit	55% (Avg. Reward)	Real-time adaptability, low overhead	Lower overall reward in batch setting

Figure 5:Model Performance Comparison

Model Suitability by Use Case

Use Case	Recommended Model	Justification
Static CTR prediction	Artificial Neural Network	High accuracy, good generalization
Lightweight, interpretable model	K-Nearest Neighbors	Simplicity and ease of implementation
Real-time adaptive ad serving	Multi-Armed Bandit	Online learning, user feedback-driven optimization

Figure 6:Model Suitability by use case

VI. CONCLUSION

This work explores and contrasts three machine learning methods—K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), and the Multi-Armed Bandit (MAB) algorithm—to recommend advertisements on a personalized basis using the Avazu Click-Through Rate (CTR) dataset. We aimed to determine the best approach in predicting user clicks and optimizing the delivery of ads in data-driven fashion.

The ANN model performed the best overall with accuracy of 83.13%, confirming its ability to model nonlinear and high-dimensional relationships present in user and ad interaction data. This renders ANN highly appropriate for static, big-data-scale classification problems like that of predicting CTR.

The simple concept of the KNN model yielded competitive performance on small datasets (82% accuracy on samples) but fell to 65% accuracy on the complete dataset because it is sensitive to data size and is not scalable. It was good enough for exploration and prototyping but not ideal for real-time or production-level recommendation systems.

The Multi-Armed Bandit (MAB) algorithm solved the problem from the perspective of reinforcement learning with adaptive ad selection aimed at maximizing cumulative user engagement. Although it obtained a lower average reward of ~55%, it was able to accurately choose high-performing ad positions (i.e., banner_pos = 0), and therefore is extremely important in online and real-time recommendation settings where continuous learning is imperative.

These points imply that while deep learning is most appropriate in static prediction and batch learning settings, methods based on MAB are most effective in real-time personalization by learning from interactive user behavior continuously. A hybrid approach that incorporates the prediction power of deep learning and the flexibility of bandit algorithms may therefore be one such direction towards developing strong, smart ad recommendation systems.

ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to "Diana", Machine Learning faculty at "The Oxford College of Engineering", for her valuable guidance, support, and encouragement throughout the course of this research. We also acknowledge the contributions of prior researchers in the field of Personalized ad recommendation system , as well as the availability of public datasets such as Multi-Armed Bandit, KNN and CTR which were useful in developing and validating our model.

REFERENCES

[1] R. Zhang, J. Zhang, and Y. Zhang, "Click-through rate prediction with deep learning: An overview," ACM Transactions on Information Systems, vol. 40, no. 3, pp. 1–36, 2022.

[2] H. Wang, F. Zhang, X. Xie, and M. Guo, "Deep learning for click-through rate prediction in online advertising," in Proceedings of the 13th ACM Conference on Recommender Systems, 2019, pp. 105–113.

[3] X. He et al., "Practical lessons from predicting clicks on ads at Facebook," in Proceedings of the 8th International Workshop on Data Mining for Online Advertising, 2014.

[4] G. Zhou et al., "Deep Interest Network for click-through rate prediction," in Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, 2018.

[5] M. B. Falahieh and H. Shokri, "A comparative study on multi-armed bandit algorithms for recommendation systems," Expert Systems with Applications, vol. 182, 2021.

[6] G. Zhou, X. Zhu, C. Song, et al., "Deep Interest Evolution Network for Click-Through Rate Prediction," Proceedings of the AAAI Conference on Artificial Intelligence, vol. 33, 2019, pp.5941–5948.

[7] Y. Feng, F. Lv, M. Qin, et al., "Deep Session Interest Network for Click-Through Rate Prediction," Proceedings of the 28th International Joint Conference on Artificial Intelligence (IJCAI), 2019, pp. 2301–2307.

[8] W. Zhang, Y. Liu, J. Wang, "An Accuracy Improving Method for Advertising Click-Through Rate Prediction Based on xDeepFM," arXiv preprint arXiv:2411.15223, 2024.

[9] P. Bouneffouf and R. Féraud, "Multi-Armed Bandits in Recommendation Systems: A Survey of the State-of-the-Art," Expert Systems with Applications, vol. 192, 2022, Art. no. 116331.

[10] J. Jayachandran, "Comparison of Multi-Armed Bandit Algorithms in Advertising Recommendation Systems," International Journal of Computer Applications, vol. 183, no. 33, 2021.