ITM Web of Conferences **73**, 01014 (2025) https://doi.org/10.1051/itmconf/20257301014
IWADI 2024

Research on Twitter User Tag Preference Prediction Based on Thompson Sampling Algorithm

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Abstract. Twitter's user behaviour data is crucial for studying user patterns and content recommendation. To achieve this goal, the paper first preprocesses a Twitter user dataset obtained from Kaggle. The dataset includes over 40,000 objects in JSON format, focusing on users who tweeted on trending topics and had at least 100 followers and were following at least 100 other accounts. This filtering helps to exclude spam and empty accounts. The study constructs a user-hashtag matrix and applies label encoding technology to convert it into a numerical matrix. The Thompson Sampling algorithm is then applied to predict user hashtag preferences. The experimental results demonstrate the remarkable effectiveness of the Thompson Sampling algorithm in predicting users' preferences for hashtags. By iteratively updating the alpha and beta parameters for each hashtag multiple times, the algorithm can accurately estimate users' preferences and successfully identify hashtags with high recommendation value. There are significant differences in the preference levels of different hashtags among user groups, providing an important basis for subsequent recommendations and push notifications. The findings validate the algorithm's effectiveness and contribute to optimizing social media content recommendation algorithms, ultimately enhancing user experience and benefiting content creators and advertisers. This research contributes to the advancement of social media platforms by improving content recommendation algorithms, enhancing user experience, and fostering a more engaging and personalized user environment.

1 Introduction

Nowadays, social media has become an integral part of people's daily lives. Twitter stands out as a leader due to its unique short-text format and rich tagging system. This helps it to attract hundreds of millions of users worldwide. By tweeting, following others, and using tags, users have created a complex information network on Twitter. This user behavior data, particularly tag data, not only reflects users' interests and preferences but also provides valuable resources for researching user behavior patterns and enhancing content recommendations.

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This study focuses on the preference analysis of Twitter user hashtag data, aiming to predict user hashtag preferences using the Thompson Sampling algorithm. To achieve this, we first preprocess the Twitter user dataset obtained from Kaggle to construct a user-hashtag matrix, apply label encoding technology to convert it into a numerical matrix, and then use the Thompson Sampling algorithm for prediction. The performance of the algorithm is evaluated through simulation experiments.

Finally, the significance of this research lies in its potential to enhance the user experience on social media platforms by providing more personalized content and services. By accurately predicting user hashtag preferences, platforms can tailor their offerings to individual users, thereby increasing user satisfaction and loyalty. Moreover, insights gained from hashtag preference analysis can help platforms understand the overall interests and trends of user groups. This, in turn, provides valuable reference information for content creators and advertisers, enabling them to promote content innovation and dissemination more effectively. Ultimately, this research contributes to the advancement of social media platforms by improving content recommendation algorithms and fostering a more engaging and personalized user experience.

1.1 Literature Review

Given the tremendous potential of Twitter user hashtag data in analysing user preferences and providing personalized content recommendations, the following section of this paper will delve into a detailed review and analysis of the current applications of Multi-Armed Bandit algorithms in recommendation systems, particularly their latest advancements in handling dynamic information and optimizing recommendation strategies. Through this literature review, we aim to provide a solid theoretical foundation and methodological guidance for our research.

‘Personalized combination recommendation method for products based on the multi-armed bandit algorithm’ introduces an innovative personalized product combination recommendation method that leverages the multi-armed bandit algorithm to optimize recommendation strategies. By comprehensively considering users' historical behaviours, product attributes, and market trends, the system can generate product combinations that better meet users' personalized needs. Experimental results indicate that this method excels in enhancing user satisfaction and purchase conversion rates, providing a new solution for personalized recommendations on e-commerce platforms[1].

‘A movie and TV works recommendation method based on the multi-armed bandit algorithm’ presents a movie and TV show recommendation system that utilizes the multi-armed bandit algorithm. By acquiring video and user features, calculating estimated rewards, and updating models based on user feedback, the system continuously optimizes its recommendation strategies. The algorithm can adapt in real-time to changes in user interests, providing users with more precise and personalized recommendations. The successful application of this system supports the digital transformation of the film and television industry[2].

‘Research on Thompson Sampling recommendation algorithm based on context-awareness’ emphasizes the balance between exploration and exploitation in recommendation systems and proposes context-aware multi-armed bandit models and Thompson Sampling techniques to address this issue. By incorporating contextual information into the recommendation strategy, the method improves the recommendation effectiveness and user experience. Experimental results validate the effectiveness of this method, providing new ideas and approaches for optimizing recommendation systems[3].

‘Fuzzy test case mutation method based on Thompson Sampling [J]. Journal of Beijing Institute of Technology’ introduces a fuzzy test case mutation method based on Thompson

Sampling, which transforms the selection of mutation operations into a multi-armed bandit problem and combines a hardware program tracing mechanism with AFL to implement the TPSFuzzer tool. Experimental results on the LAVA dataset and two real-world binary programs demonstrate that TPSFuzzer achieves higher code coverage and better testing efficiency compared to PTFuzzer, offering new ideas and techniques for fuzzy testing. The successful application of this method enhances software quality and security[4].

‘A multi-armed bandit recommendation algorithm based on content and nearest neighbor algorithm’ proposes a recommendation system that integrates content-based and nearest neighbour algorithms with the multi-armed bandit algorithm, effectively addressing the cold start problem. By combining users' historical behaviours and current interests, the system can generate more personalized recommendation lists. Additionally, the application of the multi-armed bandit algorithm allows the system to update recommendation strategies in real-time, improving recommendation accuracy and user satisfaction[5].

‘Research on personalized recommendation algorithms based on rating systems’ emphasizes the importance of recommendation systems in modern e-commerce platforms, pointing out that recommendation algorithms, as core technologies, have a significant promotional effect on product marketing. Although there are many current recommendation algorithms, they all have limitations, such as the decline in recommendation accuracy of collaborative filtering algorithms when data is sparse. In addition, this article also notes that utilizing rating information for personalized recommendations is an important research topic in current recommendation algorithm research[6].

‘Comparative study on internet recommendation systems’ comprehensively outlines the current research status and development trends of internet recommendation systems, introducing industrial demands, research institutions, journals, and conferences. It categorizes and compares mainstream recommendation algorithms, summarizing datasets, evaluation metrics, and the key challenges and difficulties in this field. Additionally, the paper proposes future research directions and trends, providing important references for the research and development of internet recommendation systems[7].

‘Multi-Armed Bandits in Recommendation Systems: A Survey of the State-of-the-Art and Future Directions’ surveys the current state-of-the-art applications of multi-armed bandit algorithms in recommendation systems and outlines future directions. It points out that recommendation systems are crucial for digital companies, directly impacting their key performance indicators (KPIs). In the big data era, the limitations of traditional batch learning have become increasingly apparent, and multi-armed bandit algorithms have gained widespread attention due to their online learning and adaptive capabilities. The paper summarizes the main applications and challenges of multi-armed bandit algorithms in recommendation systems and anticipates future research trends[8].

‘Learning the Truth in Social Networks Using Multi-Armed Bandit’ focuses on learning the time-varying true states in social networks and proposes a novel learning strategy grounded in the multi-armed bandit algorithm. Through simulation experiments, the authors demonstrate the effectiveness of this algorithm, showcasing its potential in handling dynamic information within social networks. This research not only provides a fresh perspective for social network analysis but also introduces new algorithmic ideas for dealing with similar complex systems. The application of the multi-armed bandit algorithm enables the system to explore and exploit information in the network, thereby improving the accuracy of estimating true states more effectively[9].

‘Understanding Social Media Recommendation Algorithms’ provides a comprehensive analysis of the fundamental principles of social media recommendation algorithms and their impact on information dissemination. It delves into the recommendation mechanisms of social media platforms, including user profiling, content filtering, and ranking. Additionally, the paper explores how recommendation algorithms influence the speed, scope, and impact of information dissemination, offering valuable insights into the operations of social media platforms[10].

While significant advancements have been achieved in the field of recommender systems, several challenges and gaps remain. Literature on multi-armed bandit algorithms for product recommendations often excludes the prediction and application of social media user tag preferences, and film/television recommendation methods lack in-depth exploration in this area. Additionally, while the importance of recommender systems for digital companies is acknowledged, traditional batch learning limitations are not fully addressed, and new learning paradigms are not explored. Research on social media recommendation algorithms and their impact on information dissemination also has gaps, and fuzzy testing technology faces challenges in optimizing mutation strategies and improving efficiency. Notably, there is a research void in applying multi-armed bandit algorithms to predict social media user tag preferences.

This study addresses these issues by applying the Thompson Sampling algorithm to Twitter user tag preference analysis. We optimized the algorithm, verified data accuracy, and achieved precise predictions. This research provides a basis for enhancing social media content push notifications and empirically validates Thompson Sampling's effectiveness in predicting user tag preferences, offering new insights for personalized recommender systems. Additionally, we propose an improved model, validate its effectiveness using large-scale datasets, and contribute to the development of recommender system technology.

2 Experimental Section

Through a review of the literature, we have learned that multi-armed bandit algorithms have achieved significant results in the application of recommendation systems. However, there is still relatively little research focused on predicting Twitter user tag preferences, especially using the Thompson Sampling algorithm for prediction. Therefore, this study aims to verify the effectiveness of the Thompson Sampling algorithm in predicting Twitter user tag preferences through experimental design.

2.1 Experimental Principle

In the realm of optimizing decision-making processes, Thompson Sampling emerges as a potent solution to the multi-armed bandit problem. Additionally, User-Label Matrix Construction plays a crucial role in building user profiles for predicting user preferences, and it is closely tied to our experiment.

2.1.1 Thompson Sampling Algorithm

Thompson Sampling is an algorithm for solving the multi-armed bandit problem, with its core idea being to estimate the quality of each arm (in this experiment, a "label") through sampling from a Beta distribution, thereby selecting the optimal arm for trial.

The algorithm proceeds as follows:

- Initialization: Initialize the alpha and beta parameters for each arm (label) to 1.
- Sampling: In each round, sample from the Beta(alpha, beta) distribution for each arm with non-zero alpha and beta.
- Beta distribution sampling:

$$textsamples = Beta(\alpha, \beta)$$

where α and β are the parameters for each arm (label).

- Selection: Select the arm (label) with the maximum sample value.

• Update: Based on whether the user is interested in the arm (label) (i.e., whether the corresponding position in the user's label vector is 1), update the arm's alpha or beta parameter. If the user is interested, increment the alpha parameter by 1; otherwise, increment the beta parameter by 1.

After multiple rounds of iteration, the alpha and beta parameters of each arm (label) will converge to stable values, which can be used to estimate the probability of the arm being selected (alpha / (alpha + beta)).

$$text\_probability = \alpha/(\alpha + \beta)$$

where α and β are the stable values converged after multiple rounds of iteration.

2.1.2 User-Label Matrix Construction

To convert labels into numerical form, first construct a user-label matrix. The keys of the matrix are user names (screenName), and the values are the label sets corresponding to each user (Counter objects). Then, pass all unique labels to LabelEncoder for encoding. LabelEncoder converts each label into a unique index and creates mappings from labels to indices (tag_to_index) and from indices to labels (index_to_tag).

Next, convert the user-label matrix into a numerical matrix. Create a zero list for each user with a length equal to the number of labels. Then traverse the user's label set and set the value at the corresponding index position to 1. In this way, each user is represented as a numerical vector, where 1 indicates that the user has the label corresponding to that index, and 0 otherwise.

2.2 Experimental Design

Below, we detail the experimental design, including the principles and processing of data sources, the purpose of the experiment, and the specific steps taken to conduct the study.

2.2.1 Principles and Processing of Data Sources

The database is selected from Kaggle website, which collects data on the person Twitter users follow and the hashtags they use. The data source includes over 40,000 objects in JSON format and were chosen based on the principle that these users tweeted on Twitter trending topics, and users with at least 100 followers and following at least 100 other accounts were selected in order to facilitate the filtering out of spam and empty accounts. Based on the research, the data we need required only included tags and friends content. The study aims to explore user preferences through tagged data to implement a big data push strategy. Tags reflect users' interests, focuses, and patterns. Analysing tags provides insights into user preferences, crucial for personalized recommendations. While friends' content is also important, it was not analysed deeply here to focus on tags, which are more direct and explicit. After downloading and unzipping the dataset, extract and read the csv data, set up the DataFrame and perse the tags and friends columns, parsing them from strings to lists. After this, the preprocessing of filling the missing values and data cleaning is done. Utilizing the pandas library, CSV files are ingested with the first row designated as column headers. String-type missing values within columns like tags and friends' content are replaced with empty strings, facilitating smoother processing. Duplicate entries are eliminated using the drop_duplicates method to uphold data uniqueness and integrity. Furthermore, additional cleaning steps may encompass addressing abnormal or invalid data entries and applying text preprocessing techniques to string-based data, such as tokenization, stop word removal, and stemming, to better facilitate subsequent analytical endeavours.

2.2.2 Purpose

The aim of the experiment is to study the preference of user- tagged data by Thompson Sapling algorithm, so as to implement big data push based on tagged preferences on social media. The reasons for choosing the Thompson Sampling algorithm in this paper are mainly based on its advantages in dealing with uncertainty and the exploration-exploitation tradeoff. This algorithm, by sampling from the posterior distribution, can effectively characterize the uncertainty of the environment and tend to select actions with higher potential rewards that have not been fully explored, thereby reducing sample complexity and improving learning efficiency. Especially in reinforcement learning environments, when facing the challenge of sample efficiency in interacting with the environment, the Thompson Sampling algorithm demonstrates its unique advantages. Firstly, the algorithm can handle complex uncertainty issues by continuously updating the posterior distribution to adapt to dynamic changes in the environment. Secondly, the Thompson Sampling algorithm has shown good performance in research in multiple fields, such as online advertising and recommendation systems, proving its effectiveness in practical applications. Furthermore, compared to algorithms such as Upper Confidence Bound (UCB), Thompson Sampling can provide a smoother exploration-exploitation tradeoff in some situations, avoiding issues of excessive exploration or insufficient exploitation.

By constructing a user- tags matrix to represent the user’s preference for hashtags in numerical form. Then using the multi-armed bandit, the probability of user’s preference for unseen tags could be predicted, so as to evaluate the accuracy of the algorithm’s prediction of user’s tags preference under a limited number of attempts to spiking genera, through simulation experiments.

2.2.3 Experiment Steps

During the feature extraction part, the experiment conduct a user-tags matrix, where keys are usernames (screenName), and the values are the corresponding tags sets for each user (Conter objects).

To convert these tags into numerical form:

First, Obtain all unique tags and pass them to LabelEncoder for encoding. LabelEncoder converts each tag into a unique index and creates a mapping from tags to indices (tag_to_index) and an inverse mapping from indices to tags (index_to_tag).

Second, Convert to a user-tag numerical matrix. This is done by creating a list of zeros with a length equal to the number of tags for each user. It then iterates through the user's tag set and sets the value at the corresponding index position to 1. This way, each user is represented as a numerical vector, where 1 indicates that the user has the tag corresponding to that index, and 0 indicates otherwise.

Last, Apply the Thompson Sampling algorithm. The workflow of the algorithm is as follows: Initialize the alpha and beta parameters of each tag (arm) to 1. In each round, sample each tag with non-zero alpha and beta from a Beta distribution (Beta(alpha, beta)). Select the tag (arm) with the maximum sample value and update its alpha or beta parameter based on whether the user is interested in that tag (i.e., whether the corresponding position in the user's tag vector is 1). After multiple rounds of iteration, the alpha and beta parameters of each tag will converge to stable values, which can be used to estimate the probability of the tag being selected (alpha / (alpha + beta)).

2.3 Analysis of Experimental Results

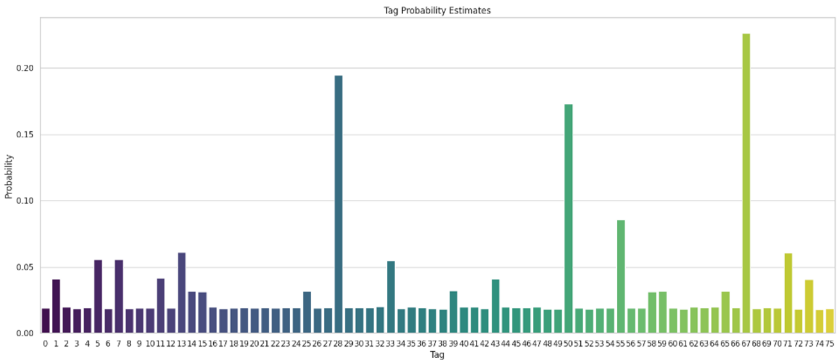

Figure 1 Bar Chart of Tags Probability.

Shown as figure 1, the horizontal axis represents different tags, using indices instead of tag names. The vertical axis represents the estimated probability of each tag being preferred by users. There are significant differences in the estimated probabilities of different tags. Some tags have high estimated probabilities, such as Tag 67, indicating that their tags are very popular among users. Conversely, some tags have low estimated probabilities, even close to 0, indicating that some of the tags are not famous or rarely used among users.

By using Thompson Sampling algorithm, through multiple iterations, the algorithm updates the alpha and beta parameters of each tag, resulting in estimated probabilities for each tag. These estimated probabilities reflect the degree of user preference for each tag and can be used for subsequent recommendations or push notifications

By implementing and applying the Thompson Sampling algorithm, we conducted a simulation experiment on user tag preferences. Specifically, we instantiated a Thompson Sampling object with the number of arms set to the number of categories in the label encoder. After that, we simulated a user experiment involving a specified number of users and rounds. In each round, we iterated over all users, selecting a tag for each based on the current user-tag matrix and the Thompson Sampling algorithm, and assigning a reward based on whether the user preferred that tag (marked as 1 in the matrix). We then updated the alpha and beta parameters of the Thompson Sampling algorithm to reflect the new estimated probabilities. After the experiment, we calculated the cumulative reward and selection accuracy, which indicated the algorithm's overall performance and accuracy in predicting user preferences, respectively.

The results showed that the Thompson Sampling algorithm performed well, with both the cumulative reward and selection accuracy reaching around 0.718. This demonstrates the algorithm's effectiveness in estimating and recommending tags based on users' historical preferences, potentially enhancing recommendation system performance and user experience in practical applications.

2.4 Findings and Conclusions

The Tompson Sampling algorithm demonstrated significant effectiveness in predicting tag preferences. The algorithm calculates cumulative reward by averaging rewards per user per round. In a 1,000-round simulation, Thompson Sampling achieved a 0.718 average cumulative reward, showing effective user preference prediction. Selection accuracy, measured by the proportion of correct tag selections, also reached 0.718, proving high accuracy in choosing user-interested tags. By iteratively updating the alpha and beta parameters for each tag multiple times, the algorithm can accurately estimate users' preferences for tags and successfully identify tags with high recommendation value. Experimental results show that there are significant differences in the preference levels of different tags among user groups. Some tags are particularly popular due to their high probability estimates, while others are less selected by users due to low probability estimates. This difference in preferences provides an important basis for subsequent recommendation and push strategies.

During the experiment, the selection of data sources and preprocessing methods had a significant impact on the results. By selecting data sources with high quality and breadth, and performing appropriate preprocessing on them, the accuracy and reliability of the algorithm can be significantly improved.

The experiment fills a research gap in the field of predicting tag preferences of social media users by applying the Thompson Sampling algorithm from the multi-armed bandit algorithm. The results validate the effectiveness of the Thompson Sampling algorithm in predicting tag preference. In the future, this algorithm is expected to be widely applied in more fields, such as personalized recommendation systems in other social media.

Although this study has achieved certain results, there are still some limitations. For example, only the numerical matrix of the first 4000 users was considered during the experiment, resulting in experimental results that may not fully represent the preferences of the entire user group. To further improve the accuracy and reliability of the algorithm, future research can consider expanding the scale of the experiment, increasing the number of users and types of tags. At the same time, attempts can be made to optimize algorithm parameter settings and data preprocessing methods to improve the convergence speed and prediction accuracy of the algorithm. In addition, the application effects of other multi-armed bandit algorithms in tag preference prediction can be explored to enrich and improve the theoretical system and practical applications in this field.

3 Conclusion

The experimental results demonstrate the remarkable effectiveness of the Thompson Sampling algorithm in predicting users' preferences for tags. By iteratively updating parameters multiple times, the algorithm can accurately identify users' preference levels for different tags and successfully filter out those with high recommendation value. In the bar chart of tag probabilities, the popularity of different tags is intuitively displayed, with some tags being widely favoured by users due to their high probability estimates, while others are less chosen due to low probability estimates. This preference difference provides an important basis for subsequent recommendation and push strategies.

This study has practical implications for social media platforms and marketers. Firstly, by accurately predicting users' tag preferences, social media platforms can provide users with more personalized content and services, thereby enhancing user experience, satisfaction, and loyalty. Secondly, the analysis of tag preferences helps platforms understand the overall interests and trends of user groups, providing valuable reference information for content creators and advertisers to more effectively promote content innovation and dissemination.

However, this study also has certain limitations. For example, during the experiment, we only considered the numerical matrix of the top 4,000 users, which may result in the experimental results not fully representing the preferences of the entire user group. To further improve the accuracy and reliability of the algorithm, future research can explore larger datasets and consider more factors that may influence users' tag preferences.

Moreover, future research can also explore the application of other multi-armed bandit algorithms in tag preference prediction, to enrich and improve the theoretical system and practical applications in this field. By continuously optimizing algorithms and expanding the scale of datasets, we can expect wider application and deeper development in the personalized recommendation systems of social media platforms.

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