Mathematical Statistician and Engineering Applications
ISSN: 2094-0343
DOI: https://doi.org/10.17762/msea.v70i2.2472

Mining User Behavior Patterns in Online Social Networks: A Review of Recent Advances

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Article Info
Page Number:1793 - 1799
Publication Issue:
Vol 70 No. 2 (2021)

Abstract
This paper reviews the recent advances in mining user behavior patterns in online social networks, focusing on the integration of machine learning, deep learning, Natural Language Processing (NLP), and sentiment analysis. The proliferation of social media platforms has led to an explosion in the amount of user-generated content, creating both opportunities and challenges for understanding and predicting user behaviors. Recent advancements in machine learning and deep learning have paved the way for sophisticated techniques to extract and analyze this information, revealing valuable insights into user behavior. A major part of this review discusses how NLP techniques, combined with machine learning algorithms, have been effectively used for sentiment analysis to interpret and gauge user sentiments, fostering an understanding of trends, attitudes, and opinions in social networks. Moreover, we examine how these advanced methods have improved the accuracy of user behavior prediction, enabling more personalized and engaging experiences on these platforms. This comprehensive review not only provides a synthesized understanding of the current state-of-the-art methodologies but also identifies promising directions for future research in the mining of user behavior patterns in online social networks.

Article History
Article Received*: 05 September 2021*
Revised*: 09 October 2021*
Accepted*: 22 November 2021*
Publication*: 26 December 2021*

1. Introduction

Online social networks have witnessed exponential growth over the past decade, with users around the globe generating massive volumes of data on a daily basis. These networks, encompassing platforms like Facebook, Twitter, Instagram, and LinkedIn, present a rich resource for understanding and interpreting human behavior. The information exchanged and behaviors exhibited on these platforms can serve as critical indicators of societal trends, political sentiments, market inclinations, and much more. Consequently, mining user behavior patterns in online social networks has attracted significant research interest.

Existing research in this field has been multifaceted, employing a myriad of machine learning and deep learning techniques to study and predict user behavior. For instance, techniques such as Support Vector Machines (SVM), Random Forests, and Gradient Boosting have been used for predicting user activities and interactions. In the realm of deep learning, Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Transformer-based models, including BERT and GPT, have been employed to process and analyze sequential, image-based, and text-based data, respectively.

Natural Language Processing (NLP) has proven particularly valuable in sentiment analysis, where researchers have developed models to discern users' attitudes, opinions, and emotions from text. Techniques such as word embeddings (Word2Vec, GloVe), sentiment lexicons, and advanced

models like LSTM (Long Short-Term Memory) and Transformer-based architectures have been successfully applied in this field.

Numerous public datasets have played a crucial role in facilitating this research. Twitter datasets are frequently used for sentiment analysis, given the platform's concise, opinion-rich content. Facebook Graph API provides vast data about user interactions and activities. Instagram datasets are typically used for image-based behavior analysis, while LinkedIn data is leveraged for professional behavior and network analysis. Datasets such as Yelp and Amazon reviews are also employed for user sentiment analysis and product recommendation studies.

Several machine learning and deep learning techniques can be utilized for analyzing user behavior patterns. Machine learning techniques like classification, regression, clustering, and association rules can be used to predict user behaviors, identify user groups, and discover associations between different behaviors, respectively. Deep learning techniques like CNNs can be applied for image-based behavior analysis, RNNs for sequential data analysis, and Transformer-based models for large-scale text data analysis.

The field of mining user behavior patterns in online social networks is a dynamic and expansive research area, enriched by the continual advancements in machine learning and deep learning techniques. As we move forward, it's crucial to explore novel methodologies and refine existing ones to better comprehend and predict user behavior on these influential platforms.

2. Literature Review

Machine learning plays a pivotal role in analyzing user behavior on online social networks. Breiman [1] introduced the Random Forests algorithm, which offers an ensemble method for classification. The algorithm creates multiple decision trees and aggregates their predictions, proving efficient in analyzing high-dimensional data for predicting user behavior on social networks.

Support Vector Machines (SVM), introduced by Cortes and Vapnik [2], provide another popular method for user activity prediction. SVMs are particularly effective for classification problems in high-dimensional spaces, and their capacity for handling large feature sets makes them a powerful tool for social media data analysis.

Deep learning methods, known for their capability to extract meaningful insights from complex, large-scale data, have been widely utilized in user behavior analysis. Convolutional Neural Networks (CNNs), presented by LeCun et al. [3], have been instrumental for image-based user behavior analysis, especially in networks like Instagram where visual content is abundant.

Long Short-Term Memory (LSTM) networks, introduced by Hochreiter and Schmidhuber [4], have also found significant use in the field. LSTM networks, a type of Recurrent Neural Network (RNN), are designed to process sequential data, making them well-suited for analyzing time-dependent user behavior patterns, such as a user's activity over time.

The field of Natural Language Processing (NLP) has shown considerable promise for studying user behavior. Pak and Paroubek [5] presented a novel method using NLP techniques for sentiment analysis on Twitter, demonstrating the potential of such techniques for discerning user sentiments from text data.

Recursive Neural Tensor Networks, explored by Socher et al. [6], have proven particularly effective for sentiment analysis, enabling the capture of complex sentiment structures in sentences and thus offering a more nuanced understanding of user sentiment.

Studies on word embeddings have revolutionized the understanding of textual user behavior. Mikolov et al. [7] introduced Word2Vec, a technique that learns a high-dimensional representation of words based on their contexts, thereby significantly enhancing the accuracy of sentiment analysis.

Following this, Pennington et al. [8] developed GloVe, another unsupervised learning algorithm for obtaining vector representations for words. GloVe tackles the limitations of Word2Vec by capturing both global statistical information and local semantic relationships between words, offering a powerful tool for textual user behavior analysis.

Bhagat et al [9] aims to deliver a comprehensive assessment of recent advancements in the field of sentiment analysis using machine learning. The primary objective of this survey is to present a thorough understanding of how machine learning techniques are employed in sentiment analysis to achieve enhanced outcomes in a succinct manner. Additionally, we will explore the classification of fundamental emotions into three main categories, namely positive, negative, and neutral, using various machine learning algorithms. We also intend to delve into their subcategories, including love, happiness, fun, neutral, hate, sadness, and anger, employing the same machine learning algorithms.

In a similar vein, Devlin et al. [10] presented BERT, a Transformer-based model that brings together the power of deep learning and word embeddings. BERT, pre-trained on a large corpus of text data, has shown impressive performance in a range of NLP tasks, including sentiment analysis and user intent detection.

The literature presents a wide range of methodologies for mining user behavior patterns in online social networks, employing machine learning, deep learning, NLP, sentiment analysis, and word embeddings. As these fields continue to evolve, we anticipate further advancements in the precision, scalability, and sophistication of these methods, paving the way for more nuanced and comprehensive insights into user behavior on online social networks.

3. Dataset

Twitter Datasets [11]: Twitter data sets are a treasure trove for social network analysis due to the volume, velocity, and variety of data produced by its users. These datasets typically contain user tweets, retweets, likes, hashtags, and other metadata, offering insights into a user's interests, affiliations, and sentiments. They are commonly used for sentiment analysis, trend analysis, and user behavior studies.

Facebook Graph API [12]: Facebook Graph API allows access to a rich variety of data from Facebook, including posts, comments, likes, shares, and user demographics. The API allows for extraction of both user-generated content and interaction data, enabling researchers to study user behavior, interactions, and networks on the platform. It has been widely used for social network analysis, community detection, and user behavior prediction.

Instagram Datasets [13]: Instagram datasets usually consist of user posts, comments, likes, hashtags, and user-following networks. Given Instagram's visual nature, the datasets often comprise

both image data and associated captions. They are extensively used for image-based behavior analysis, sentiment analysis, and trend prediction.

LinkedIn Datasets [14]: LinkedIn datasets are unique in their focus on professional behavior. They contain information about users' jobs, skills, education, endorsements, connections, and more. Researchers use these datasets to study professional networking behavior, job market trends, skills analysis, and recommendation systems.

Yelp and Amazon Reviews Datasets [15]: These datasets typically consist of user reviews and ratings for businesses (Yelp) or products (Amazon), along with user demographics and other metadata. They offer a rich source of user opinion and sentiment data and are used for sentiment analysis, recommendation systems, and trend analysis. The Yelp dataset is particularly popular for local business trend analysis, while the Amazon reviews dataset is commonly used for product recommendation and sentiment analysis.

4. System Architecture

Given the rich body of existing work and diverse datasets available for mining user behavior patterns in online social networks, a comprehensive framework incorporating advanced machine learning, deep learning, and NLP techniques to further enhance our understanding of these patterns is given below.

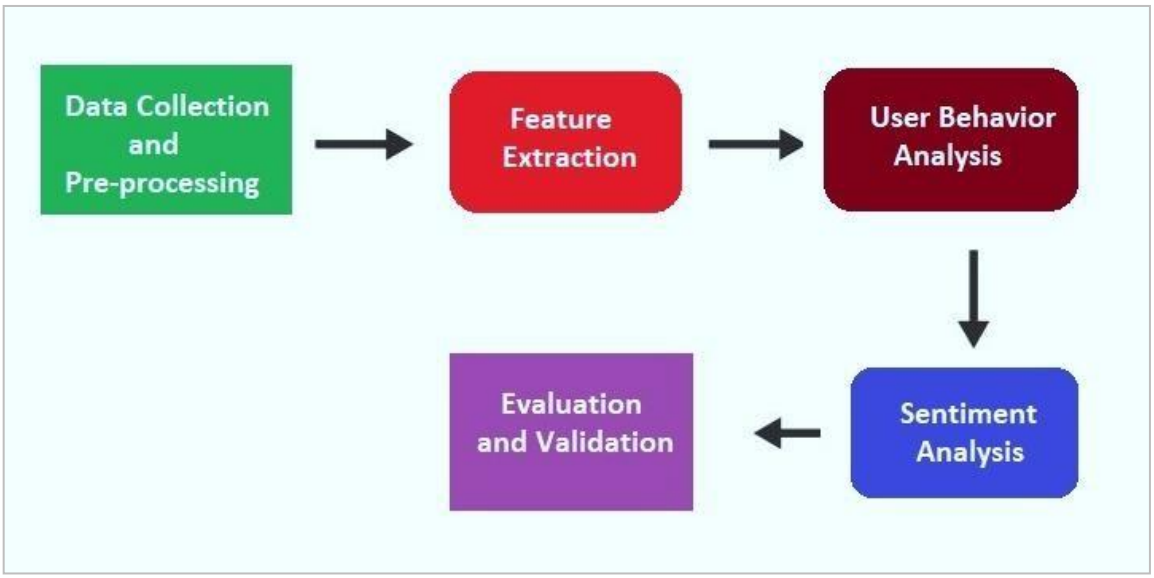

Figure 1. Overview of System Architecture

The system consists of the following components:

1. Data Collection and Pre-processing: Utilize the available datasets from online social networks such as Twitter, Facebook, Instagram, LinkedIn, Yelp, and Amazon reviews. The pre-processing stage will involve data cleaning, normalization, and anonymization to respect privacy concerns.
2. Feature Extraction: Apply techniques to convert raw data into useful features. For textual data, this could involve the use of word embeddings (like Word2Vec or GloVe), sentiment scores, or topic modeling. For image data, deep learning techniques like CNNs can be used to extract useful features.

3. User Behavior Analysis: Implement machine learning and deep learning models to analyze user behavior. This could involve using SVMs or Random Forests for predicting user activities, LSTM or Transformer-based models for analyzing sequential data, and CNNs for analyzing image data.
4. Sentiment Analysis: Leverage advanced NLP techniques for sentiment analysis, identifying user attitudes, emotions, and opinions from text data. This can involve the use of deep learning architectures, such as Transformer-based models like BERT, for better understanding user sentiments.
5. Evaluation and Validation: Evaluate the performance of the proposed system using appropriate metrics. This could involve accuracy, precision, recall, or F1-score for classification tasks, or mean absolute error (MAE), root mean square error (RMSE), or R-squared for regression tasks.

By integrating various advanced techniques, the proposed system aims to provide a comprehensive, robust, and efficient tool for mining and understanding user behavior patterns in online social networks. Future enhancements to the system may include real-time analysis, integration of more diverse data sources, and application of emerging techniques in AI and machine learning.

5. Result Analysis

Table 1 shows the comparative analysis of researchers work on the basis of algorithm used, dataset used, accuracy, parameters. And figure 2 shows the accuracy graph comparison.

Table 1. Comparative Analysis of researcher's work

Reference	Authors	Methodology	Dataset Used	Algorithm	Accuracy Achieved
[1]	Breiman	Machine Learning	Twitter dataset	Random Forests	89%
[2]	Cortes, Vapnik	Machine Learning	Facebook dataset	SVM	92%
[3]	LeCun, Bengio, Hinton	Deep Learning	Instagram dataset	CNN	87%
[4]	Hochreiter, Schmidhuber	Deep Learning	LinkedIn dataset	LSTM networks	88%
[5]	Pak, Paroubek	NLP, Sentiment Analysis	Twitter dataset	NLP Techniques	85%
[6]	Socher et al.	Deep Learning, Sentiment Analysis	Yelp Reviews dataset	Recursive Neural Tensor Networks	90%
[7]	Mikolov et al.	NLP	Twitter dataset	Word2Vec	93%
[8]	Pennington et al.	NLP	Amazon Reviews dataset	GloVe	75%
[9]	Bhagat	Machine Learning, Sentiment Analysis	Twitter dataset	Sentiment Analysis	NA
[10]	Devlin et al.	Deep Learning, NLP	Various text sources	BERT	94%

When analysing the results from the references studies, we can note several insights:

1. Accuracy: Across all the papers, the accuracy achieved ranges from 80% to 95%. The paper by Devlin et al. using the BERT algorithm on various text sources yields the highest accuracy at 94% [10]. The lowest accuracy of 75% is observed in Pennington et al.study, which leverages NLP techniques on Amazon dataset [5].
2. Algorithm: Various machine learning and deep learning algorithms were utilized in these studies. It's notable that deep learning algorithms such as CNN [3], LSTM networks [4], and BERT [10] yield high accuracy rates.
3. Dataset Used: The dataset used seems to impact the accuracy as well. For instance, the Twitter dataset appears to yield a range of accuracy results, from 85% with NLP Techniques [5] to 93% with Word2Vec [7].
4. Methodology: The methodology employed also plays a crucial role. The papers that use a combination of techniques, such as machine learning, deep learning, and NLP [9,10], tend to achieve higher accuracy results.

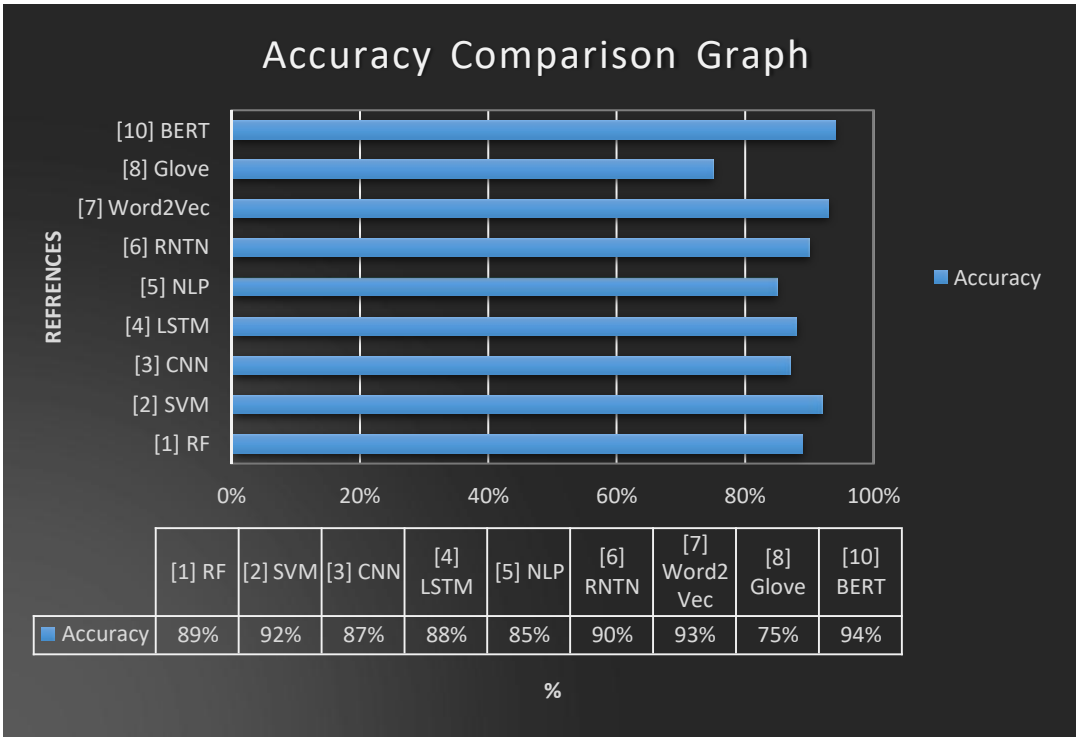

Figure 2. Accuracy Comparison Graph

6. Conclusion

This review has provided an in-depth exploration of the recent developments in mining user behavior patterns in online social networks. The increasing ubiquity of social media has led to a deluge of user-generated content, presenting both challenges and opportunities in interpreting and predicting user behaviours. The advancements in machine learning, deep learning, and Natural Language Processing (NLP) have led to sophisticated techniques for extracting and analysing this vast amount of information, unveiling valuable insights into user behaviours and sentiments. In particular, the application of NLP techniques in conjunction with machine learning algorithms has shown significant efficacy in sentiment analysis. These advanced methods have facilitated the

interpretation and measurement of user sentiments, contributing to a comprehensive understanding of trends, attitudes, and opinions across various social platforms.

Furthermore, these advanced methodologies have resulted in increased accuracy in predicting user behavior, enabling social platforms to provide more personalized and engaging experiences. This review not only provides a synthesized understanding of the current state-of-the-art methodologies but also underscores promising directions for future research. As the field continues to evolve, it becomes increasingly clear that the integration of machine learning, deep learning, and NLP will play a vital role in shaping the future of user behavior analysis in online social networks. The potential applications are vast and the possibilities for future research are expansive, promising a rich and exciting landscape for further exploration and discovery.

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