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ANALYSIS AND PREDICTION OF USER BEHAVIOR IN SOCIAL NETWORKS USING MACHINE LEARNING AND ENCODERS TECHNIQUES

The article discusses the problem of analyzing and predicting user behavior in social networks by building models of user behavior using machine learning methods. Social networks are complex systems in which user interactions form multifaceted dynamics and allow you to obtain many results that require the use of effective algorithms for data processing. The main goal of the study is to develop an approach that allows you to identify behavioral patterns, assess the level of audience engagement, and predict user reactions to different types of content.

The study identified key factors influencing user behavior, including social interactions: response to content, activity time, and metrics collected during the collection of information. The use of of One-Hot, Label, Target, and Count encoders made it possible to create a model that can adapt to changing conditions and improve the speed and effectiveness of the model, while providing accurate forecasts.

The results of the study demonstrated the effectiveness of the proposed model for determining the dependence of audience engagement on the type of content, as well as for identifying the most influential parameters for analyzing user behavior in social networks. using several different encoders to process textual categories of user behavior on social networks.

The findings are important for the further development of big data analysis tools in social networks, as well as for optimizing interactions between users and social networks. The proposed approach can be used in social behavior research, the development of recommendation systems, and content management in dynamic environments.

Key words: *social networks, user behavior, feature encoders, categorization, machine learning.*

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АНАЛІЗ ТА ПРОГНОЗУВАННЯ ПОВЕДІНКИ КОРИСТУВАЧІВ У СОЦІАЛЬНИХ МЕРЕЖАХ ЗА ДОПОМОГОЮ МАШИННОГО НАВЧАННЯ ТА КОДУВАЛЬНИХ МЕТОДИК

У статті розглядається проблема аналізу та прогнозування поведінки користувачів у соціальних мережах шляхом побудови моделей поведінки користувачів із використанням методів машинного навчання. Соціальні мережі є складними системами, в яких взаємодії користувачів формують багатогранну динаміку та дозволяють отримати чимало результатів, які потребують застосування ефективних алгоритмів для опрацювання даних.

Основною метою дослідження є розробка підходу, який дозволяє ідентифікувати поведінкові патерни, оцінювати рівень залученості аудиторії та прогнозувати реакції користувачів на різні типи контенту.

У ході дослідження були визначені ключові фактори, що впливають на поведінку користувачів, зокрема соціальні взаємодії: реакція на контент, час активності та метрики зібраних під час збору інформації. Застосування кодувальників дозволило створити модель, здатну адаптуватися до змінних умов та удосконалити швидкодію та результативність моделі і при тому надавати точні прогнози.

Результати дослідження продемонстрували ефективність запропонованої моделі для визначення залежності залученості аудиторії від типу контенту, а також для виявлення найбільш впливових параметрів для аналізу поведінки користувачів у соціальних мережах. Це дає змогу адаптувати стратегії взаємодії з аудиторією, покращувати якість рекомендаційних систем та підвищувати ефективність прогнозування та виявлення трендів. Крім того, здійснено порівняння отриманих результатів із використанням кількох різних кодувальників для обробки текстових категорій поведінки користувачів у соціальних мережах.

Отримані висновки є важливими для подальшого розвитку інструментів аналізу великих даних у соціальних мережах, а також для оптимізації взаємодії між користувачами та соціальними мережами. Запропонований підхід може бути використаний у дослідженнях соціальної поведінки, розробці рекомендаційних систем та управлінні контентом у динамічних середовищах.

Ключові слова: *соціальні мережі, поведінка користувачів, кодувальники, категоризація, машинне навчання.*

Problem statement

In today's world, social networks have become an integral part of the lives of millions of people, influencing communication, information sharing and decision-making. Given the huge amount of data generated by users every day, there is a need to create effective approaches to analyze their behavior. Studying user interactions, their preferences, and their impact on other network participants are key aspects of modern research.

One promising way to present data is to categorize user behavior, which allows you to automate the analysis of large amounts of data, find hidden patterns, and make accurate predictions.

Categorization techniques open up new possibilities for modeling user behavior in the extremely dynamic environment of social networks, given the complexity of the relationships between users and the diversity of their activity.

This article is devoted to the study of approaches to determining the most effective way to classify user behavior patterns through the use of encoders in the developed system. It also considers key methods and technologies that allow you to analyze user interaction, assess their level of engagement, and predict future trends. The results obtained can become the basis for the development of intelligent systems that help to better understand the needs of users and make informed decisions in the field of social media.

Related Works

Recent research in the field of analyzing user behavior in social networks actively uses machine learning methods to model and predict the dynamics of interactions. In particular, much of the work focuses on developing models to identify patterns of behavior, such as changes in engagement rates, content distribution, and interaction between users. An important area is also the study of the impact of content on user behavior and the possibility of automated analysis of emotional reactions through machine learning models [1].

One of the key aspects of recent research is the use of deep learning to recognize patterns in user behavior data. In particular, neural networks have been successfully used to predict future user actions, such as likes, comments, shares of publications and subscriptions. Research shows that deep models can identify dependencies in user behavior with high accuracy, allowing for more accurate predictions about their future actions.

Another area that is actively developing is related to agent-based modeling (ABM), which allows you to reproduce individual strategies and actions of users on social networks. Such models make it possible to study how interactions between users can change the behavior of groups within the network, in particular, how changes in one element can affect the overall dynamics [2–3].

Graph models are also used to study social interactions in networks, where each user is treated as a node and their interactions are treated as edges of the graph. This approach allows you to identify social influences, communities, and important connections in the network [4]. Research shows that graph models are effectively used to analyze the evolution of social networks, as well as to predict trends in the spread of information.

Significant progress has also been made in the field of time series modeling. Using prediction techniques such as LSTM (Long Short-Term Memory), scientists can investigate changes in user behavior over time, allowing them to predict changes in their activity or mood by analyzing past data.

It is also worth noting the integration of social interaction modeling in machine learning systems to create adaptive models that respond to changing social contexts [5–6]. This allows you to automatically adjust interaction strategies depending on user reactions and behavior.

The paper [7] investigates methods for encoding categorical data, such as One-Hot Encoding, Label Encoding, Target Encoding. The authors argue that the choice of coding method significantly affects the quality of predictions in machine learning models, especially in the medical field.

A new deep learning method for encoding categorical features was also investigated in the work [8]. The authors suggest using embedded representations (embeddings) instead of traditional methods such as One-Hot or Label Encoding for more efficient analysis of categorical data in machine learning models. Deep embedded representations of categorical features improve the quality of model prediction and can significantly reduce the dimensionality of data.

Thus, modern research in the field of modeling user behavior in social networks actively uses the latest machine learning technologies, which allows for deeper analysis of interactions, predicting behavior, and finding new ways to optimize user engagement strategies.

Formulation of the purpose of the study

Despite significant progress in the study of user behavior on social networks, there are still aspects that need further study and improvement. An example would be the analysis of individual user behavior rather than group behavior. Usually, in research, there is an analysis of group models and insufficient attention is paid to the development of personalized models to predict the actions of individual users.

In addition, the models studied rarely take into account the influence of cultural, linguistic, and regional characteristics on user behavior, which limits their effectiveness on a global scale. Another example would be the study of dynamic user behavior and reactions to content and its impact on user behavior in real time remains a poorly studied area due to the complexity of the factors influencing them.

Also, existing models often inefficiently predict new trends, especially those that appear suddenly and spread in non-standard ways. There is also no insufficiently automated process for classifying users according to behavioral patterns. It is also worth paying attention to research focused on negative behavior, such as trolling or spreading misinformation, which is still not sufficiently studied.

Solving these problems will contribute to the creation of more complex and effective user behavior models that take into account the diversity and complexity of social networks.

Presentation of the main material of the study

Social networks are dynamic systems in which users actively interact with each other, create, distribute and consume content. Analyzing user behavior in such environments is a complex task that requires many factors to be taken into account, such as engagement rates, social interactions, emotional reactions, and content impact. In the face of large amounts of data and their complexity, traditional approaches to analysis become less effective, while machine learning methods open up new opportunities for building dynamic behavior models.

The main purpose of the article is to develop an approach to categorizing dynamic models of user behavior in social networks using coders. To achieve this goal, you need to identify the main factors that influence user behavior on social networks, including their engagement, activity, and reaction to content. There is also a need to analyze modern encoders that can be used to build dynamic behavior models. In addition, it is necessary to develop a model architecture that combines big data processing, time series analysis, and machine learning-based forecasting. The next step is to evaluate the effectiveness of the proposed model based on real data from social networks and demonstrate the possibility of adapting the model to solve problems in the field of social networks.

Thus, the article aims to create a process that allows you to better understand the dynamics of user behavior on social networks and use this knowledge to make informed decisions.

The proposed technique uses coders to determine user behavior patterns based on factors such as content type, engagement and popularity factors, and user behavior. In addition, encoders can also be used to convert unstructured data into numerical vectors, detect bots and fraudulent accounts. Also, the use of this method will help improve content personalization and work well with analytics of the emotional component of comments on social networks. The data goes through a pre-processing stage, where the categorical variables are converted using One-Hot Encoding, after which the data is separated into training and test sets. Next, three main models are applied: Random Forest, Decision Tree and Gradient Boosting, which will be trained on training data and then tested on test data. To evaluate the performance of the models, MAE and R^2 metrics are used, as well as cross-validation to ensure the stability of the results. Each model gives different forecasts that are compared with each other based on the specified metrics, which allows you to choose the most effective model for further use.

Static methods of user behavior on social networks help to formalize the model that users usually use when using social networks during the performance of a specific action. As opposed to template user behavior models, which can model user behavior over time or how it can change over time. In addition, such models can show which people will change their behavior under the influence of published content and react to events in the future.

In this way, it is possible to make predictions of future events based on current or past ones. It is then possible to investigate how interest in a particular publication increases and when there is a decline in activity or interest in that information.

One of the approaches to working with dynamic models is machine learning and deep learning: using recurrent neural networks (RNNs) or transformers, it is possible to process and predict user action sequences, and classification or clustering algorithms can be used to segment users and predict their behavior.

By combining different approaches, you can create more accurate and comprehensive models, taking into account the frequency of interactions and publications, the audience engagement factor, the popularity factor of the post on social networks, the audience retention rate, and the content impact factor [9].

Also equally important is the description of the qualitative parameters collected from social networks, namely the typology of users, the topic of content, and the influence of users. In addition, the level of engagement and tone of interactions must be taken into account. When studying dynamic models of user behavior, such parameters are influential. The combination of quantitative and qualitative parameters allows you to create a flexible and accurate model of user behavior, which allows you to make predictions and analyze various scenarios of interaction on social networks.

Table 1

Reflection of the dependence of factors of engagement, popularity and auditor retention rate on the content topic

Selected model parameters	News Content	Commercial activity	Personal content	Content distribution	Social interaction
Audience engagement factor	25 %	20 %	30 %	50 %	40 %
Post popularity factor	250 000	300 000	100 000	500 000	400 000
Audience retention rate	60 %	45 %	70 %	65 %	75 %
Content Impact Factor	500 000	400 000	300 000	600 000	550 000
Engagement Rate	15 %	10 %	20 %	30 %	25 %
Content type	*Information* (Info)	Promotional (Promo)	Personal	Viral	Discussion

According to Table 1 there is a certain pattern of topics from the collected metrics with categorical variable Content type. For instance, the audience engagement factor, which shows how actively users interact with a certain type of content, viral content affects the most. With this type of content, user activity is mostly aimed at distributing content. Thus, it can be assumed that there is a direct relationship in the calculated metrics. It can be seen that content focused on social interaction, such as polls, discussions, or events, provides the highest level of audience engagement.

Otherwise, personal content includes posts about the user's life, emotions, and experiences, also generates significant interest and interaction. Commercial content demonstrates a moderate level of engagement, which can grow with high-quality presentation or an interactive format. News content attracts attention mainly depending on the relevance of the events that are covered.

The lowest engagement rate is observed for posts that do not stimulate active discussion or interaction, such as standard ads or information that does not elicit an emotional response.

The graph shows that increasing the level of engagement is closely related to the relevance, emotional richness and interactivity of content, which confirms the importance of the correct selection of the format of publications to achieve maximum audience activity.

To categorize using feature engineering based on the collected parameters, it is important to consider each of the provided attributes and determine what new features can be created to improve the modeling results. Previously, Table 1 already has formalized data on the type of content and defined numerical characteristics (for example, the number of views, reach), as well as some text categories (content type) have been allocated.

One of the well-known approaches to creating new features for this kind of problem is the processing of numerical features. This approach involves the use of each of the numerical parameters collected from the numerical parameters, which will help to form new features based on their relationships or statistical characteristics.

First of all, a large difference in numerical values is taken into account, then it is possible to normalize or standardize these features in order to avoid their distortion in the process of training the model.

The next situation may be to calculate the relative value between the number of views to the number of comments or likes and the reach of the audience to the number of posts. Another case is to calculate the difference between the maximum and minimum values to calculate the level of variability of content.

If we consider the informational type of content, which works mostly with textual content, it is needed to apply techniques for processing categorical variables. For example, One-Hot Encoding or Label Encoding. One-Hot Encoding is responsible for creating binary features for each category. For example, Content Information Type → (1, 0, 0, 0, 0) or Promotional Content Type → (0, 1, 0, 0, 0). As opposed to Label Encoding. This method is characterized by assigning numerical values to each category.

For more complex models, it is created features that combine numerical and categorical parameters. For example, it is created a new feature that represents how the type of content affects the number of views and explore the interaction between the type of content and the number of views.

Also, we can calculate an average for each type of content for numerical parameters, such as the number of views or reach. This will allow you to group into categories and see how different types of content interact with other features.

Another approach to categorization is the calculation of statistical indicators. For example, calculating the median and average for each type of content or coefficient of variation, that is, the ratio of the standard deviation to the mean to determine the degree of variability.

If examine the collected data about the time of publication or the time of publication of content during the day, you can create time-based temporal attributes based on the day of the week, time of day, or season. All the collected parameters will only complement and clarify the existing model.

When researching text categories of content type, using Label Encoding, it is possible to make comparisons not only by converting each text into a unique number. On the other hand, Target Encoding is used to research the target audience by replacing each text with the average of the corresponding target variables and compare it with Count Encoding, which is used to replace text categories with the number of their occurrences in the data.

This algorithm processes a dataset with various content types and their associated numerical values to predict "Engagement Level". The data is encoded using four methods: One-Hot Encoding, Label Encoding, Target Encoding, and Count Encoding. Numerical columns are normalized using min-max scaling to ensure all features are on the same scale. Standard Scaling is applied to the features before splitting the data into training and testing sets. Random Forest Regressor, Decision Tree Regressor, and Gradient Boosting Regressor machine learning models are trained and evaluated using Mean Absolute Error (MAE) and R^2 score. The results for each encoding method and model are stored for comparison. MAE comparison and correlation heatmaps for feature relationships visualizes in bar plot. As a result it is identified the best encoding method and model combination for predicting Engagement Level. The MAE formula calculates the average absolute error between predicted and actual values. R^2 score shows how well the model explains variability.

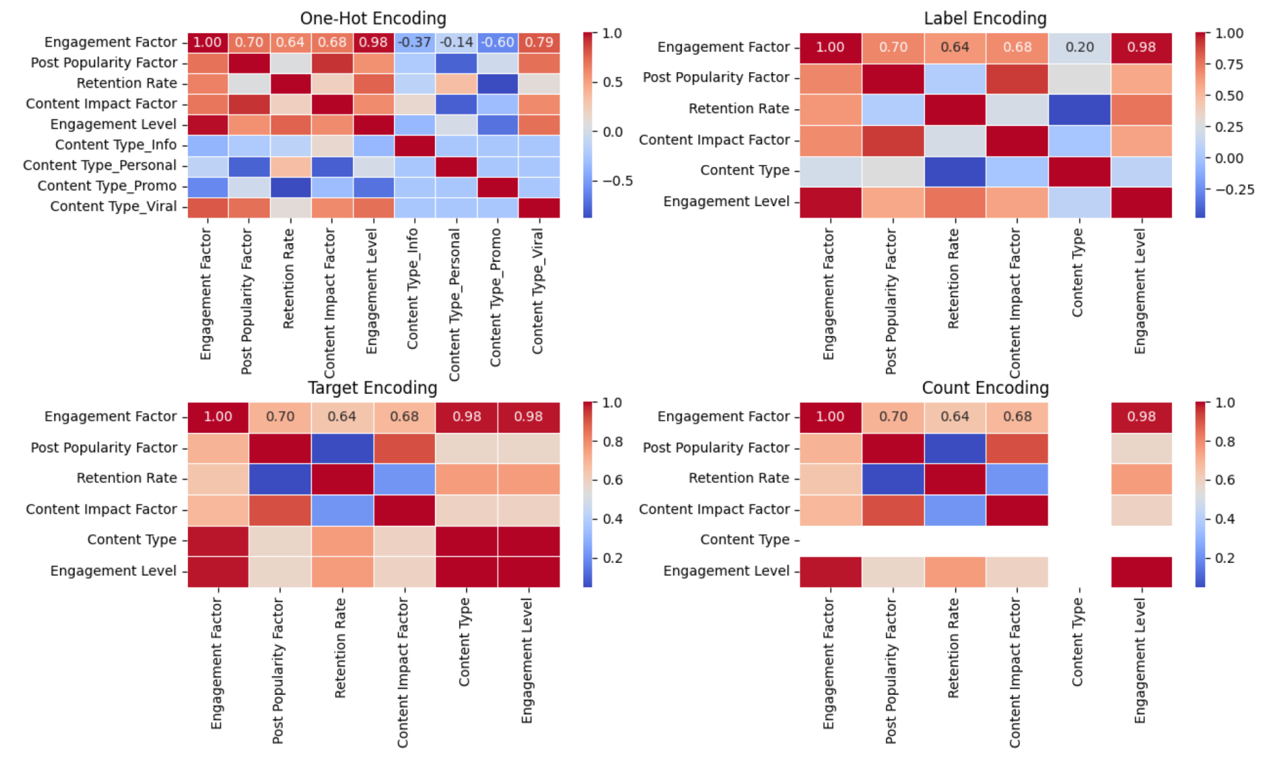

Fig. 1. Comparison result of One-Hot, Label, Target, and Count encoders based on text content types

Count Encoding can be empty for Content Type because it replaces categories with their frequencies, which can result in the same values for different categories and low correlation. Instead, One-Hot Encoding divides categories into separate binary columns, allowing us to clearly see how each category correlates with other variables.

Fig. 1 presents correlation matrices for four categorical variable encoding methods: One-Hot Encoding, Label Encoding, Target Encoding, and Count Encoding. One-Hot Encoding has almost no effect on the correlations between variables because each category receives a separate column and the values are binary (0 or 1). This reduces the influence of categorical variables on the overall data structure, but leads to an increase in the dimensionality of the matrix.

In contrast to One-Hot Encoding, Label Encoding creates artificial correlations between categorical and numerical variables, since the categories are represented by numbers that do not have a logical order. As a result, this method can distort real dependencies in the data.

Target Encoding shows the highest correlations, especially between content type and engagement rates. This is because the categories are replaced by the average value of the target variable. This approach can improve the quality of the model, but there is a risk of data leakage if the encoding is performed incorrectly.

Count Encoding works similarly to Target Encoding, but instead of the average target value, it uses the frequency of occurrence of each category. This allows you to store information about the distribution of values without a significant risk of data leakage, but can still affect the correlation between variables.

So, One-Hot Encoding is a safe choice if you want to avoid changing correlations between variables, however, it can increase the dimensionality of the data. Label Encoding should be used with caution due to possible artificial correlations. Target Encoding provides the best results for machine learning models but needs to control data leakage. Count Encoding is a compromise option that helps store important information without a significant risk of dependency distortion.

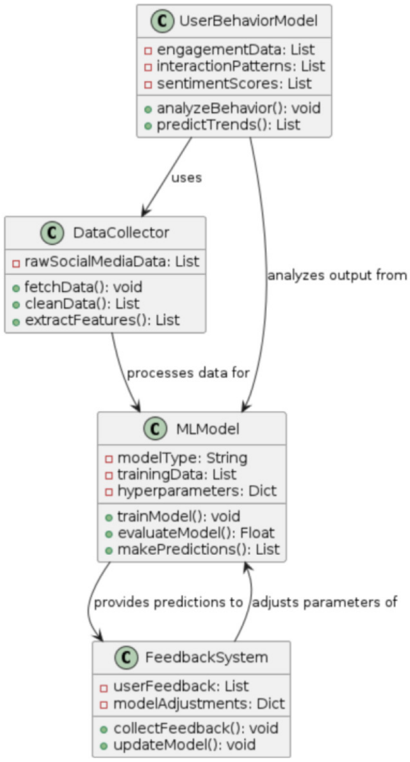

Fig. 2. UML diagram of the application of machine learning in a dynamic model of user behavior

From Fig. 2 you can see the functional component of the chosen machine learning approach. The user behavior model is the central element on the basis of which the analysis of user actions and the prediction of their activity is carried out. Its attributes include engagement data, interaction patterns, and sentiment scores.

The next component of the chart is data collection, which is responsible for saving data from social networks. Such a process involves processing raw data, including cleaning and extracting key data characteristics for further processing.

Another step describes the machine learning model that performs the basic processing. It has parameters that include model type, training data, and settings (hyperparameters). In addition, using a machine learning model, you can make predictions, evaluate performance, and perform model training.

The feedback system allows you to improve the model with the help of collected user feedback and the selection of settings parameters to improve the model. Thus, a cyclical process is formed, where the system constantly improves its accuracy based on new data.

The model makes predictions by learning the relationships between input features (engagement factor, post popularity and so on) and the target variable (engagement level) during training. Once it is trained, the model applies these learned patterns to new data to estimate the target variable, effectively generalizing from historical examples. The accuracy of these predictions is measured based on metrics Mean Absolute Error (MAE). In this way we are ensuring the model reliably forecasts engagement levels for new inputs. This implementation is used Python programming language along with libraries such as numpy, pandas, matplotlib, seaborn, and scikit-learn for data manipulation, model training, and evaluation.

To reduce MAE for results from Fig. 3, tune hyperparameters are used with GridSearchCV or RandomizedSearchCV, enhance features through interaction terms, polynomial features and feature selection. Consider using advanced models

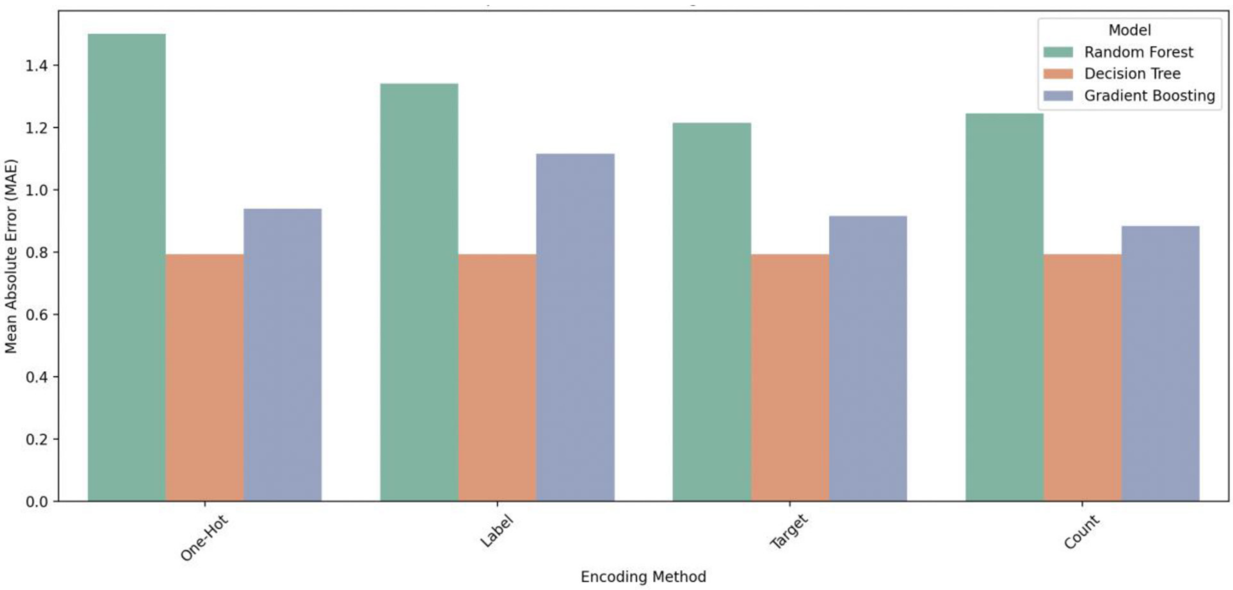

Fig. 3. MAE comparison across encoding methods and models

like XGBoost or LightGBM, and implement cross-validation for more reliable performance estimates. Additionally, scale or normalize your data, apply ensemble methods, and handle outliers to improve model accuracy.

Conclusions

An approach to creating models of user behavior in social networks using machine learning was proposed, which allows solving the problems of analyzing complex interactions and predicting. Users' behavior on social media depends on many factors, such as engagement, reaction to content, and social connections, which form the main patterns of their activity. The use of machine learning methods shows high efficiency in detecting hidden patterns in large amounts of data. The developed model takes into account various parameters of behavioral metrics and provides an in-depth and comprehensive analysis of user actions. The model successfully predicts user actions, such as interacting with posts, commenting, and distributing content, which shows its reliability and accuracy. One-Hot encoding, while efficient, increased dimensionality and potentially led to overfitting. While Label Encoding is simple, it led to ordinal relationships that would negatively impact model performance. Target encoding has shown promise, especially for decision trees, but can be risky due to overfitting if not properly tested. Count Encoding works well with Decision Trees, offering an efficient representation by encoding categories based on their frequencies. Ultimately, decision trees performed best with all encoding methods, but require tuning. The developed approach has practical value in analyzing trends, developing content strategies and creating recommendation systems. The use of such models contributes to more effective management of interaction with the audience, allowing companies to better adapt to the needs of their users.

Thus, the study confirmed that the application of machine learning to analyze user behavior is a promising direction. In the future, such models can be improved by integrating new tools and taking into account new trends in social networks.

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