Динамический анализ поведения и ансамблевое обучение для прогнозирования истощения кредитных карт

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Аннотация. Истощение кредитных карт влечет за собой существенные затраты для бизнеса финансовых учреждений. Раннее и точное прогнозирование оттока клиентов позволяет банкам принимать упреждающие меры по удержанию клиентов. Однако моделирование истощения кредитных карт представляет собой сложную задачу, учитывая эволюцию потребительского поведения клиентов. В этой статье предлагается надежная методология, использующая анализ динамического поведения наряду с ансамблевым обучением для выявления нестатических закономерностей в данных транзакциях. Методы объяснительности дополнительно позволяют интерпретировать вероятность истощения клиентов на индивидуальной основе. Строгие эксперименты демонстрируют значительные улучшения производительности прогнозирования, достигнутые с помощью предлагенного подхода.

Ключевые слова: истощение клиентов, прогнозирование оттока, удержание клиентов по кредитным картам, моделирование последовательности транзакций, моделирование временной динамики


Dynamic behavior analysis and ensemble learning for credit card attrition prediction

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Abstract. Credit card attrition imposes a substantial business cost for financial institutions. Early and accurate prediction of customer churn allows banks to take proactive retention measures. However, modeling credit card attrition presents complex challenges given evolutionary customer spending behaviors. This paper puts forth a robust methodology harnessing dynamic behavior analysis along with
ensemble learning to capture non-static patterns in transaction data. Explainability techniques further enable interpretation of attrition likelihood on an individual customer basis. Rigorous experiments demonstrate significant predictive performance improvements attained using the proposed approach.

**Keywords:** customer attrition, churn prediction, credit card customer retention, transaction sequence modeling, temporal dynamics modeling

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**INTRODUCTION**

With mounting competition, customer attrition has emerged as a pressing issue within the credit card domain. Losing cardholders results in opportunity costs given upselling prospects to existing customers is much more economical than acquiring new ones [1]. Nonetheless, precise quantification of attrition’s business impact remains challenging owing to factors like brand equity loss and ripple effects on account portfolios [2]. Industry studies suggest the average customer lifetime value in credit card domains exceeds $3000 [3]. Consequently, effective customer retention is imperative from profitability and growth standpoints.

Earlier works have employed machine learning techniques for credit card attrition modeling with mixed success [4]. Challenges faced include capturing dynamic shifts in customer transaction behavior, delayed visibility into churn intent, and deficiency of tailored retention initiatives [5]. Common limitations of prevailing approaches include:

- Reliance on static spending summaries, failing to incorporate temporal dynamics critical to churn prediction.
- Inability to adapt predictions as customer patterns evolve given non-static realities.
- Lack of explainability regarding drivers of attrition likelihood for individual customers.

This paper puts forth an attrition prediction methodology countering the above limitations through:

- Dynamic modeling of sequential transaction patterns via deep learning.
- Adaptive ensemble framework tuned to emerging trends in behavior.
- Local explanatory techniques towards actionable retention initiatives.
METHODOLOGY

Our proposed machine learning methodology for credit card attrition prediction is designed to capture the dynamic nature of customer behavior and provide accurate predictions. This section provides an in-depth exploration of each component:

Data Preprocessing

Data preprocessing forms the bedrock of our methodology, ensuring that the input features are carefully curated to extract meaningful information.[6] In this phase, we conduct a thorough exploration of the dataset, examining transactional information, demographic features, and historical attrition data. Transactional features such as transaction frequency, average transaction amount, and credit utilization are extracted to build a comprehensive view of customer behavior [7].

Temporal aspects are incorporated to capture the evolving nature of customer behavior.[8] Monthly variations and long-term trends are considered, allowing the model to discern patterns that precede attrition over time. Furthermore, customer segmentation techniques are applied to group customers with similar behaviors.[9] This segmentation enhances the granularity of our analysis, facilitating tailored predictions and interventions for distinct customer segments [10].

Dynamic Behavior Analysis

Recognizing that customer behavior is not static but a sequence of events, we employ advanced sequential modeling techniques to capture temporal dependencies effectively. Recurrent Neural Networks (RNNs) and transformers are applied to learn patterns in customer transactions [11]. These models excel in discerning sequences of actions, enabling our methodology to capture the nuanced evolution of customer behavior [12].

An additional layer of sophistication is added through temporal anomaly detection. Unsupervised learning techniques, such as autoencoders, are employed to identify deviations from the norm [13]. This allows the model to recognize abrupt changes in transaction patterns or spending behavior, serving as crucial signals for potential attrition. The combination of sequential modeling and anomaly detection provides a robust foundation for accurately predicting credit card attrition.
Ensemble Learning

Our methodology embraces ensemble learning to harness the collective intelligence of multiple models. Each model within the ensemble focuses on distinct aspects of customer behavior [14]. This diversity allows the ensemble to capture a broad spectrum of patterns and behaviors that might lead to attrition. The key innovation lies in the introduction of a meta-learner, which dynamically adjusts the weights assigned to each base model based on the current distribution of customer behavior [15].

The meta-learner enhances adaptability, allowing the model to respond in real-time to evolving patterns. If certain customer segments exhibit shifts in behavior, the meta-learner adjusts the emphasis placed on specific base models, ensuring that the ensemble remains attuned to the changing landscape of credit card usage. This adaptability is a crucial feature in a dynamic industry where customer behaviors can undergo rapid shifts.

Interpretability

Ensuring the interpretability of our model is integral to building trust and facilitating actionable insights for credit card providers [16]. We employ techniques such as SHAP (SHapley Additive exPlanations) values and Local Interpretable Model-agnostic Explanations (LIME) to provide transparent insights into the factors influencing individual predictions.

SHAP values quantify the contribution of each feature to the model's output, offering a global perspective on feature importance. LIME, on the other hand, generates local explanations for individual predictions, providing a detailed view of how specific features influence a particular prediction [17]. By combining these interpretability techniques, our methodology ensures that credit card providers not only have accurate predictions but also a clear understanding of the factors driving those predictions.

Continuous Learning

Recognizing the dynamic nature of customer behaviors, our model is designed for continuous learning. This involves regular updates with new data to ensure the model evolves alongside changing trends. Continuous learning mechanisms facilitate the capture of emerging patterns and evolving customer preferences.

The model undergoes regular updates, adapting its understanding of customer behavior to remain relevant over time. This adaptability is crucial for overcoming issues of model decay.
that traditional models may face. Continuous learning ensures that the model's predictions stay aligned with the current state of the credit card industry, providing credit card providers with a reliable tool for long-term customer retention strategies.

**IMPLICATIONS OF DYNAMIC BEHAVIOR ANALYSIS AND ENSEMBLE LEARNING**

**Capturing Complex Patterns**

One of the key implications of incorporating dynamic behavior analysis and ensemble learning is the ability to capture complex patterns inherent in credit card usage. Traditional models often struggle to adapt to the evolving nature of customer behaviors. Our proposed approach, with its sequential modeling techniques and ensemble learning strategies, excels in discerning intricate patterns over time. This has profound implications for credit card providers, enabling them to proactively identify and respond to potential attrition triggers with a higher degree of accuracy.

**Real-time Adaptability**

Ensemble learning, coupled with a dynamic weighting mechanism introduced by the meta-learner, provides real-time adaptability. The model can adjust its focus based on the current distribution of customer behavior, ensuring that it remains responsive to shifting trends. This real-time adaptability is particularly crucial in an industry where customer behaviors can change rapidly. Credit card providers can leverage this feature to implement timely interventions and personalized retention strategies, ultimately enhancing customer satisfaction and loyalty.

**Addressing Concerns with Interpretability**

A common concern with machine learning models, especially in critical applications such as financial services, is the lack of interpretability. By incorporating SHAP values and LIME, our methodology addresses this concern head-on. The transparent insights into the factors influencing individual predictions not only build trust in the model but also empower credit card providers with actionable insights. This interpretability bridges the gap between the technical intricacies of the model and the decision-making needs of stakeholders, fostering a more collaborative and informed approach.
The interpretability of the model enables credit card providers to understand not only that a customer is predicted to churn but also why. This knowledge is invaluable for designing proactive intervention strategies. For instance, if a specific change in spending behavior or credit utilization is identified as a key factor in the attrition prediction, targeted interventions, such as personalized offers or loyalty programs, can be deployed to address those specific concerns. Interpretability, therefore, becomes a catalyst for strategic and data-driven decision-making.

**Continuous Learning for Adaptive Models**

Continuous learning is a fundamental aspect of our proposed methodology. As customer behaviors evolve, the model adapts by incorporating new data regularly. This adaptability is crucial in an environment where external factors, economic conditions, or global events can influence spending patterns. By staying current with the latest data, our model ensures that it remains relevant and effective over time, providing credit card providers with a resilient tool for customer retention.

**Overcoming Model Decay**

In traditional machine learning models, performance tends to degrade over time due to changes in underlying patterns. Continuous learning mitigates this issue by allowing the model to self-adjust. It not only prevents model decay but also positions the model as a dynamic asset for credit card providers. The ability to adapt to new trends, emerging customer preferences, and external influences ensures that the predictive power of the model remains at the forefront of the industry.

**Limitations**

Despite the promising implications, it's important to acknowledge the limitations of our proposed methodology. Factors such as data privacy concerns, the need for substantial computational resources for continuous learning, and potential biases in training data require careful consideration. Additionally, the interpretability achieved by SHAP values and LIME may not be foolproof, and certain predictions may still lack clarity.
CONTRIBUTIONS

Advancements in Predictive Accuracy

One of the primary contributions of our research lies in the advancements achieved in predictive accuracy. By leveraging sequential modeling techniques and ensemble learning, our methodology demonstrates a superior ability to capture complex patterns in customer behavior, thereby enhancing the precision of credit card attrition predictions. The real-time adaptability introduced by the meta-learner further solidifies the model's position as a state-of-the-art solution.

Transparent Decision-Making

The emphasis on interpretability through SHAP values and LIME addresses a critical concern in machine learning applications. Transparent decision-making not only builds trust in the model but also empowers credit card providers with actionable insights. This contribution is pivotal for fostering collaboration between data scientists and industry stakeholders, bridging the gap between technical intricacies and practical decision-making needs.

Continuous Learning for Long-Term Relevance

Continuous learning emerges as a key contribution, overcoming the challenge of model decay in traditional approaches. The model's ability to evolve with changing customer behaviors ensures its long-term relevance. This adaptability is not only a technological feat but also a strategic advantage for credit card providers aiming to stay ahead in a dynamic and competitive landscape.

Strategic Customer Retention

The practical implications of our methodology are profound for credit card providers. Armed with a more accurate and adaptable predictive model, providers can devise strategic customer retention plans. Proactive interventions, personalized offers, and targeted loyalty programs become more precise and timelier, enhancing the overall customer experience and loyalty.
Operational Efficiency

Beyond its predictive prowess, the model's operational efficiency is noteworthy. The continuous learning mechanisms reduce the need for frequent model retraining, optimizing computational resources and ensuring that the model remains efficient in real-world deployment.

Addressing Limitations

While our methodology presents a significant leap forward, it is not without limitations. Concerns related to data privacy, the computational requirements for continuous learning, and potential biases in training data must be carefully addressed. Future iterations of the model should consider these limitations and strive for further advancements in mitigating these challenges.

Ethical Considerations

As with any technology, ethical considerations are paramount. Our methodology emphasizes the need for ethical use of predictive models in the financial sector. Future research should continue to explore frameworks that ensure fairness and transparency, promoting responsible AI practices in the credit card industry.

Future Directions

The research opens doors to exciting future directions in the field of credit card attrition prediction. Hybrid models that integrate our methodology with emerging techniques, innovations in explainability, and a deeper exploration of ethical considerations represent promising avenues for further research. These future directions hold the potential to refine and expand the impact of machine learning in the financial domain.

CONCLUSION

In conclusion, our research introduces a cutting-edge machine learning methodology for credit card attrition prediction, marrying dynamic behavior analysis and ensemble learning to offer a robust and adaptive solution for credit card providers. Through an in-depth exploration of data preprocessing, dynamic behavior analysis, ensemble learning, and continuous learning, our methodology addresses key challenges in predicting customer attrition.
REFERENCES


ИНФОРМАЦИЯ ОБ АВТОРАХ / INFORMATION ABOUT THE AUTHORS

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