

AI-Driven Decision Support for Credit Risk Prediction using MVC based Hybrid Recommender System

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Abstract: The rapid expansion of digital lending platforms and the growing complexity of financial institutions require intelligent, resilient, scalable and efficient credit risk assessment and management systems. The traditional systems for credit risk assessment often prioritize predictive accuracy as the performance metric while overlooking the system-level efficiency and intelligent real time decision support. In order to improve computational performance and personalized real-time financial decision-making, this study proposes a hybrid framework that integrates the Model View Controller (MVC) architecture with data-driven analytics and recommender systems.

The MVC architecture separates the application into model view and controller. The model layer is a business logic layer which processes client requests sent to a server. The view layer is a presentation logic layer which is mostly used for interaction with users in an effective way. Controller is a servlet which maps resources of the application with the requirements of the clients.

This architecture reduces the application latency, enhancing the performance of the web application handling the financial data. The credit risk classification engine receives the user data, and the outcomes are then fed into a hybrid recommender system to produce tailored financial recommendations. By integrating decision-support systems, predictive analytics, and architectural optimization into a unified framework, this research has practical implications for modern financial applications.

Keywords:

Credit Risk, MVC, Financial Analytics, Recommender Systems, Decision Support, Web Architecture

1. Introduction

Nowadays credit cards have become an easy payment mechanism for buying goods and services in online/offline markets. This increasing popularity of credit cards poses several challenges on the part of financial institutions and banks. This includes assessing a customer before issuance of the loan or processing the loan application. The inevitable events such as COVID-19 , war, inflation, recessions can affect the customer's stability status and increase the risk of non-performing assets (Chang et al.,2024). Thus this economic stability of the financial landscape demands not only predicting the credit risks but also a continuous monitoring of the borrowers.

Credit risk assessment and evaluation is the essential task to measure customer credit worthiness in order to quantify the financial risks associated with the financial organisations. This involves a strategic plan in order to have a 360 degree view of the borrower and making informed decisions in real time scenarios. A resilient and responsive lending framework is required in the light of data intensive banking and fintech institutions that require both computational efficiency and accuracy.

The credit scoring techniques have evolved from statistical techniques/models to machine learning based techniques. Recent studies also indicate that the machine learning and deep learning models have surpassed the performance of the statistical models (Kanaparthi, 2024). There are three specific and critical requirements for modern financial web applications:

- Efficient data processing under high load
- Accurate risk prediction
- Personalized decision support

The existing systems typically address these requirements in isolation which may affect the overall credit risk assessment task. This study proposes a unified framework that integrates:

- An optimized server-side architecture (MVC)
- Analytical risk classification
- Personalized recommendation mechanisms

Thereby improving both system performance and predictive reliability.

2. Literature Review

The methods driven by data have replaced statistical methods in credit risk modeling. The interpretability of logistic regression and related models was a major reason behind their popularity, but they were not able to address the challenges associated with large-scale datasets and non-linear correlations (Hand & Henley, 1997). Recommender systems have turned out to be an indispensable tool for providing personalised suggestions and have found applications in several domains from entertainment, e-commerce, healthcare, trading gastronomy and finance (Adomavicius & Tuzhilin, 2005; Ricci et al., 2015). Personalised approaches utilise customer profiles including their transaction histories, behavioural patterns, psychometric data, indicative of their preferences and choices (Pathi, 2025). Recent works also indicate that the use of explainable AI can further enhance the transparency as compared to the traditional black-box machine learning models (Bussmann, 2020).

The predictive performance has been enhanced by machine learning techniques, but many studies ignore the system-level efficiency over the predictive accuracy of the model (Lessmann et al., 2015).

The MVC design pattern for the software architectural view has been widely adopted due to the modular or separation of concerns feature (Gamma et al., 1994). MVC architecture is a modular design approach that decomposes the application into three layers: model, view and controller while decoupling the business logic, presentation and data respectively. This clear separation makes the architecture robust in terms of testing, development and maintenance of large scale web applications. The present study extends this architectural concept by integrating it with financial analytics and

recommender systems, forming a comprehensive framework for intelligent financial applications.

3. Recommender systems

Recommender systems help customers or financial institutions to choose among a variety of options/choices, thereby supporting the credit risk decisions. Generally, the RS algorithms can be classified into two broad categories: personalized and non-personalized (Ekstrand et al., 2010), wherein personalized algorithms recommend the financial services like loan credit card etc based on the user/customer profiles or preferences while in non-personalised algorithms the same set of recommendations are provided irrespective of the customer attributes.

3.1 Collaborative filtering [CF] based techniques

The collaborative filtering [CF] techniques are based on the similarity principle. They assume that the customers having similar fintech profiles are likely to exhibit similar behaviour/actions in the future too. These techniques are based on the intuition of identifying the users similar to that of the target user “Alice” and using their risk profiles to predict the unknown risk profiles of the target user “Alice”. Collaborative filtering methods are either memory based or model-based methods (Ekstrand et al., 2010). Memory based methods are also known as neighborhood based collaborative filtering algorithms which can be user-based or item-based. In user based CF, the similarity between target customer/borrower and every other customer/borrower is computed and the most similar borrowers' profiles are used for generating recommendations. In item-based CF, the similarity between a specific type of loan and every other loan is computed and the most similar rated loans by the user are used for generating recommendations. In model based methods either data mining or machine learning model or Large language models (LLMs) are used to represent the user preferences and generate predictions on the basis of the learned model. CF techniques inherently suffer from the cold start problem with respect to both the new users and new items.

3.2 Content based [CB] techniques

In content based [CB] filtering methods, the customer's own financial profile is used for generating recommendations. The recommendation depends upon the match between the rich user profile and the loan/credit card specific properties which are known with respect to each loan/credit card . The customer's profile can include one's income, employment status, credit history, repayment record, debts, transaction time, and spending patterns. For example if a customer "*Bob*" has stable/regular income, low debts or EMI burden and good repayment history then he is likely to get low-risk loan approval, high credit limit and a premium credit card as recommendations. This method suffers from the problem of overspecialization wherein the user may get similar kinds of recommendations lacking the serendipic/surprise element .Given the current limitation, handling cold start problems of new customers with no initial financial profile and preferences may not receive appropriate recommendations as per his choice(Ricci et al., 2015).

3.3 Hybrid recommendation techniques

Hybrid systems were introduced to overcome the limitations that existed with the traditional approaches such as sparsity and cold start issues According to (Burke, 2007) , key hybridization patterns include:

Weighted hybrid: In this different weights are used for predictions from collaborative and content-based algorithms. In order to create a final risk score, for instance, a borrower's debt ratio, income stability, and repayment history may be paired with default trends of comparable borrowers.

Switching hybrid: In this depending on the availability of data, the system alternates between collaborative and content based approach. Content-based approaches are employed when a client is new and has no prior financial experience. Collaborative filtering works better if there is a sound transaction history and repayment records available.

Feature-combination and feature-augmentation: utilize one recommender's outputs as input attributes for a different model. For example, an SVM or machine

learning classifier may incorporate collaborative filtering results as additional characteristics or features for final credit approval.

Cascade: Credit card/loan applicants are first filtered by one model, and the resulting recommendation is then improved by the second model. For instance, a knowledge-based model eliminates applicants who violate banking norms and then collaborative filtering ranks the remaining candidates according to the risk level.

Meta-level hybrid models use the entire output model of one recommender as input for another. Collaborative filtering can be used to improve borrower similarity analysis after a content-based customer profile has been created.

3.4 Knowledge based [KB] techniques

These techniques rely on the user's requirements that are most often taken as a part of user interaction by the system. It uses knowledge from the financial experts while considering the RBI guidelines, lending policies, credit approval rules, financial compliances. The knowledge based recommender systems may involve case based or constraint based approaches (Aggarwal, 2016). While the constraint-based approach takes the user-specified constraints into account when generating suggestions, the case-based approach compares the case to the cases already stored in the case base.

4. Proposed Hybrid Framework

The framework consists of three interconnected layers:

4.1 MVC Architectural Layer :

The MVC design is a layered partition of server-side executable components, it is separated into the following three components for easier maintenance and optimization:

4.1.1 Model: This layer is made up of business logic components that essentially handle user requests. It runs on the server, interacts with the necessary data layer, and provides the user with a response.

4.1.2 View: Presentation logic is rendered by this layer. primarily in charge of interacting with users to gather requests and communicate responses.

4.1.3. Controller: The controller is a dispatcher servlet that functions as a resource mapper in the server. It receives client requests and maps them to the necessary view or model component, which the server then executes.

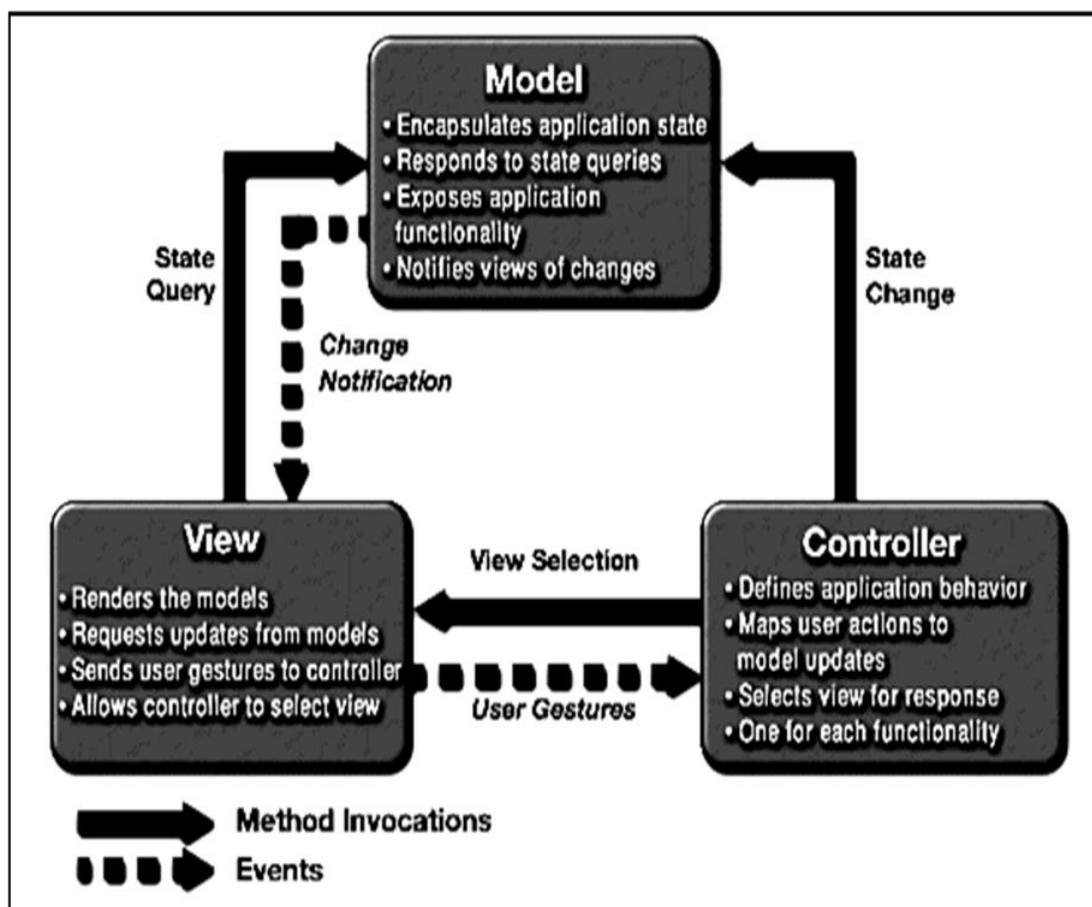


Figure 1: MVC Architecture (Thung et al., 2010)

4.2 Analytical Layer

The analytical layer takes in the validated data from the architectural layer and processes it further using machine learning classifiers to classify the risk into high risk, medium risk and low risk classes. (Lai, 2023) utilised both traditional features; including demographics ,transaction profiles, spending time, mobile usage, social profile and non-

traditional features; including psychological traits, behaviour patterns for more accurate and real time predictions.

4.3 Recommendation Layer

The recommendation layer is responsible for generating personalised suggestions based on the classification results generated by the analytical layer. It uses a rule based engine consisting of predefined rule sets for each of the classification results. It also utilises content based filtering techniques while scanning other similar borrower profiles, attributes, preferences, payment behaviour etc and then recommending the same financial advice. This hybrid approach that combines rule based and content based filtering adds personalisation while generating risk aware recommendations.

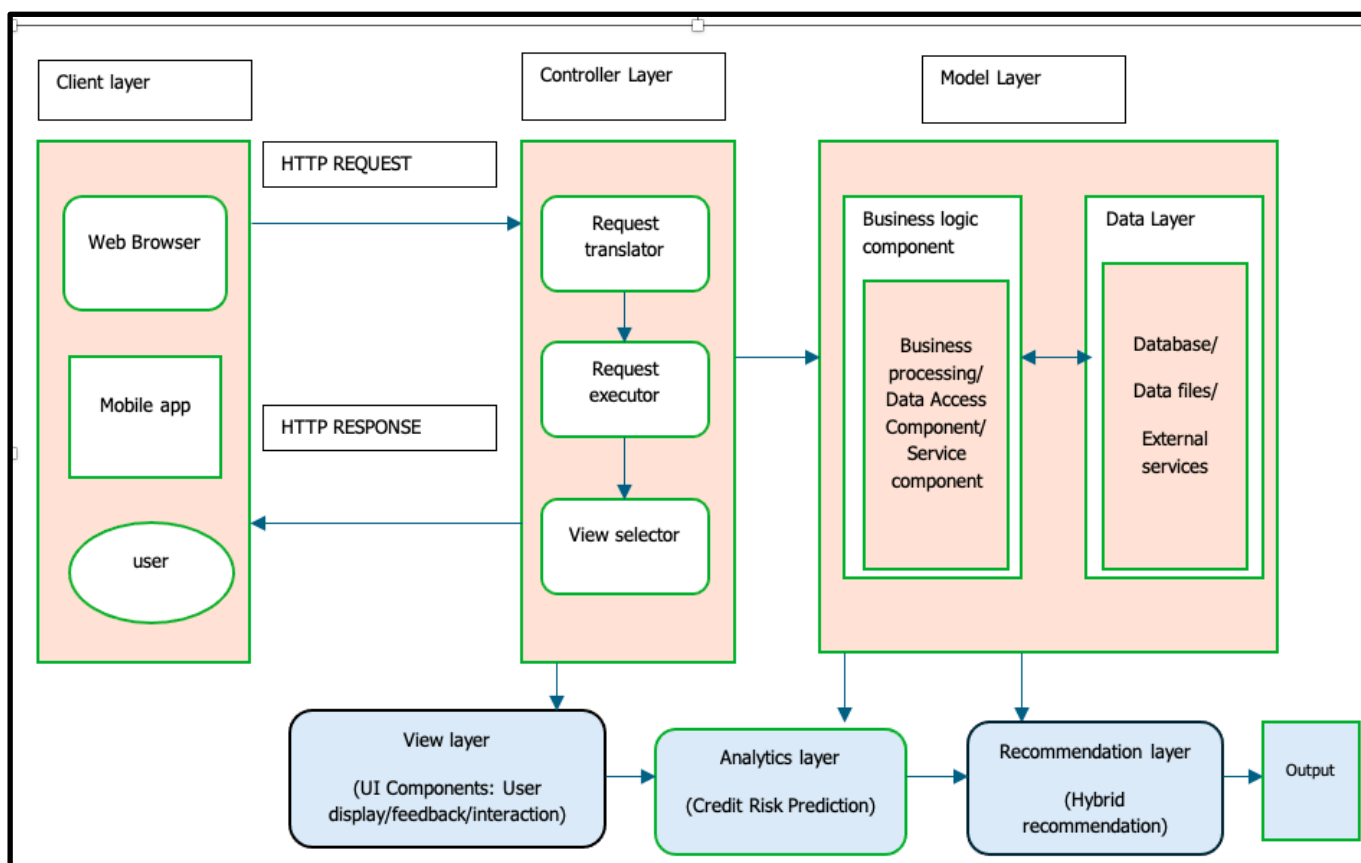


Figure 2: Proposed framework using MVC based Hybrid Recommender System

5. Conclusion

This study emphasises the fact that efficient system architecture, reliable risk analysis and personalised recommendations integrated in a cohesive framework can bring out a scalable system that fits in the dynamic digital lending environment. With the use of MVC architecture, the system becomes more efficient in terms of scalability and maintenance. In addition, the analytical layer categorises borrowers into various risk groups by taking into account a broader variety of criteria, such as behavioral patterns in addition to conventional financial indicators. Lastly, the hybrid recommender system, goes one step further by transforming forecasts into usable and personalised recommendations that users and financial institutions can actually act upon.

The end result is a hybrid framework that facilitates more intelligent and individualized decision-making in addition to risk prediction. This is particularly crucial in practical situations where quick, precise, and customized financial judgments are required.

Looking ahead, there is scope to make the system even more effective by adding explainability features so that users can better understand how decisions are made, and by incorporating real-time data streams for continuous monitoring. Testing the framework on larger, real-world datasets would also help in validating its practical impact.

In essence, this work highlights a shift toward more balanced and user-aware financial systems—ones that are not just technically strong, but also responsive and helpful in guiding better financial choices.

6. References

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